HUMAN CAPITAL, DECISION-MAKING AND PERFORMANCE

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HUMAN CAPITAL, DECISION-MAKING AND PERFORMANCE

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SUMMARY

This dissertation investigates how human capital influences decision-making and performance at the firm- and household-level. It has three empirical studies. The first two essays focus on the firm-level managerial human capital. We discuss how to measure the leadership's human capital precisely, and how it affects corporate innovation and productivity. The third one analyzes how household heads' personality traits influence risky investment decisions.

The first two essays focus on firm-level study. The first one investigates how a firm's managerial human capital influence its total factor productivity (TFP) via the potential channels of technology progress and efficiency improvement. As the main operation participants, we use the CEO's previous experiences and the composition of the top management team (TMT) to enrich the measures of their human capital. We find that CEO's management vitality and innovative incentives promote TFP, while TMT's diversity impedes TFP.

In the second essay, we further explore whether a firm's innovation incentive is the bridge to link managerial human capital and higher productivity. As the major decision-makers, we consider the human capital of the CEO and board of directors (BOD), using similar proxies in the first essay to measure it. The results imply that CEO and BOD's career experiences in various functions, as well as some special experiences, all influence their innovation incentives.

To give a broad picture of human capital measurement and its impacts on different levels of the national economy, we shift to household-level research in the third essay. We investigate how household head's risk attitude in different domains, general and financial, influences the investment decision on different types of financial products. We find that risk-averse persons are more reluctant to invest in risky assets and allocate less wealth on them as well, with a more notable impact on riskier assets. Additionally, financial risk attitude reacts more sensitive towards market turbulence than in the general domain.

CHAPTER 1

INTRODUCTION

Human capital has prolonged impact on different aspects of national economy, from individual-level to firm-level. Besides the objective constraints and conditions, human being plays a more important role in economic activities through decision-making and action-taking. As the important economy participants, strategies taken by the corporations and households would largely influence the wealth accumulation, social welfare, market regulation and so on. Therefore, investigating how their human capital is accumulated and measured would be of great value.

This dissertation therefore investigates the human capital measurement by discussing how it is gained. The first two essays explore the measurement of leadership's human capital at firm-level. Unlike the general employee's human capital, decision-makers' human capital plays crucial roles in strategic decision and daily operation. Therefore, for the decision-makers or top executives, some specific aspects of their human capital, such as leadership, collaboration ability, etc., are way more important rather than the general human capital. In this sense, their managerial human capital cannot be simply measured by their demographic characteristics or general experiences, which is widely discussed, because they only explain a small proportion of the human capital formation. We thus adopt some special experiences to better measure leadership's managerial human capital, enriching the measurement proxies. These special experiences include the overseas experiences, government backgrounds, and most importantly, career experiences in various functions.

In these two firm-level studies, we use the main database China Stock Market and Accounting Research (CSMAR) with the sample of publicly listed manufacturing firms in China, covering the post-crisis period 2008-2016. In the empirical analysis, we assume CEO appointment process is a matching of CEO's special experiences to firm's objective needs. One crucial issue is that, based on the panel data structure, decision-makers and executives' special experiences rarely change overtime due to the nature of dummy variables. The traditional methods to address the endogeneity issue, which are Fixed Effect (within method) and First-Difference estimations, are thus not the optimal strategies. Therefore, we adopt the RE-IV method with Hausman-Taylor instruments (finding instruments within the panel system, which are time-demeaned time-variant regressors) to address the endogeneity caused by CEO appointment. We also control the persistent trend of TFP and R&D investment by constructing a dynamic specification. It helps us to see the impacts of CEO, BOD and TMT's human capital on firm's innovation incentives and performance in a long-run framework. To address a similar endogeneity issue in dynamic view, we expand the Hausman-Taylor RE-IV method in the baseline, borrowing the idea from system-GMM to search for extra instrument.

We further expand our human capital research to the household-level in the third essay. To measure household heads' risk attitude in different domains, we use test-based indicator to proxy for the general risk attitude, and use the self-reported debt tolerance level to measure the risk attitude in finance facet. We explore the impacts of risk attitude in these two domains from both the aspects of long-run investment propensity and the instantaneous financial behaviors under a special market condition. We adopt the Probit estimation for long-run propensity, and use the Tobit method for instantaneous investment propensity and depth. Additionally, we broaden the research scope to the heterogeneous impacts of risk attitude on different financial products with different levels of uncertainty.

We make the following contributions to the firm- and household-level human capital research. First of all, besides the demographic factors and general experiences, we enrich the measures of managerial human capital by also considering CEO, BOD and TMT's experience-based indicators, including overseas, government and functional backgrounds. These proxies better reflect leaders' specific unobservable human capital factors, such as cognitive skills, managerial abilities, risk preference, etc.. Second, instead of only focusing on a single person or a team, we consider a firm's aggregated managerial human capital by taking both individual- and team-level factors into account. In R&D investment strategy, CEO and BOD are both considered by referring to their roles played in decision-making process, while in promoting productivity, CEO and TMT's managerial human capital is taken into account due to their duty of practical implementation. Finally, rather than targeting at the financial outcomes, we step further to provide a practical way (TFP) to achieve higher profitability, giving more practical implications.

The rest of dissertation is structured as follows: Chapter 2 discusses whether CEO's human capital and TMT composition, reflected by the experience-based indicators, can improve firm's productivity. Chapter 3 presents the relationship between CEO/BOD's human capital and firm's innovation propensity. Chapter 4 investigates how household heads' risk attitude in both general and finance domains influence households' stock and fund investment. Chapter 5 concludes.

CHAPTER 2

LEADERSHIP'S HUMAN CAPITAL AND CORPORATE TOTAL FACTOR PRODUCTIVITY

2.1 Introduction

Raising productivity to spur profitability is the main goal of manufacturing firms. Besides increasing the input quantity, raising the remaining unexplained part of productivity, which is the total factor productivity (TFP), is the fundamental driving force to achieve the long-run growth. Two major channels that lead to higher TFP are efficiency promotion and technology progress. The former refers to both production and management efficiency, influenced by input quality, governance structure and management strategies. The latter is related to a firm's propensity and capacity to innovate, as well as the technology spillovers.

Many papers thus investigated the determinants and influencing factors of a firm's productivity (Syverson, 2004; Smarzynska Javorcik, 2004). The internal factors include the quality of production inputs, R&D devotion, firm structure, etc. (Aw et al., 2008). Externally speaking, technology spillovers, market competition, international trade, and relevant policy all contribute to the TFP growth (Cassiman et al., 2010). Leadership and general staffs also play the important roles in operation, so their impacts on firm performance received growing attention in recent years (Schmitz, 2005; Bandiera et al., 2020).

For general human capital, skilled workforce promotes firm's R&D efforts and efficiency, thus spurring productivity (Tang and Wang, 2019). As the efficient methods to improve general or specific skills of the workforce, on-job training and work-life programs have positive impacts on productivity (Konrad and Mangel, 2000). Besides the average level, skill composition in the workforce also influences productivity. Autonomous groups, team collaboration, and hierarchy dissolution all contribute to TFP (Zwick, 2004). Ethnicity, education, and demographic diversity all potentially influence productivity (Iranzo et al., 2008; Parrotta et al., 2014).

Although many papers realize the importance of leadership in strategic planning, operation supervision and practical implementation, most of them only focus on the managerial practice or control power (Chang and Hong, 2019). Measured by executives' shareholdings, the managerial ownership is positively related to the productivity in terms of a larger control power (Palia and Lichtenberg, 1999). High-quality managerial practices and talents, measured by managers' info on the operations, monitoring, targets, and incentives, all drive productivity (Syverson, 2011). Unfortunately, seldom of these papers discuss the relevant topic by targeting on the managerial human capital, such as executives' managerial skills, cognitive ability, and personality.

To explore the influencing factors of productivity also has applicable significance in China. Due to a diminished demographic dividend with a declining trend of labor force ratio, the labor cost in China kept growing after the financial crisis 2008.[1] As a result, the price competitiveness of "made-in-China" products in the world market reduced, causing a shrinking market demand. Moreover, many Chinese firms still engage in the lower-end of the production chain, producing, processing, and assembling factor-intensive products with low value-added and technical content. In recent years, Chinese manufacturing firms realized that TFP is the key to sustainability, thus devoting more to the technology promotion. In this context, investigating how to build an innovative and efficient production system is of great value in Chinese case. Among all influencing factors, the notable importance of managerial human capital should not be neglected. Therefore, in this chapter, we investigate the importance of managerial human capital in firm's productivity promotion in the context of Chinese manufacturing industry.

[1]Based on the report of Oxford Economics, the annual salary of a representative worker in China is 1500 RMB in 2009 but becomes 4000 RMB at the end of 2016.

2.2 Theoretical Framework

Based on the existing literature (Griliches, 1979; Syverson, 2011), to make the exposition clearly, we assume a multiplicatively separable expression of productivity:

$$Y = A \cdot F(K, L, M) \tag{2.1}$$

Y is the overall production output. $F(.)$ is a production function of production input quantities of three major factors for manufacturing firms, which are capital stock K, labor input L, and intermediates M, respectively. $F(.)$ increases monotonically with a diminishing marginal return, so we have $F'(.) > 0$ and $F''(.) < 0$.

The factor-neutral shifter A is defined as the TFP. It captures the remaining part of productivity unexplained by the input quantity. TFP has many sources due to its inclusion of all ignorance, so we express it as:

$$TFP = A(T, G; v) \tag{2.2}$$

T and G are two major sources, which are technology progress and efficiency improvement. v is a composited error, including all other sources, unobserved heterogeneous and idiosyncratic error.

Efficiency G depends on a series of operation and production practices. From management aspect, it is affected by managers' ability to attract, integrate, and allocate resources, as well as lead and coordinate production process. From production aspect, it depends on workforce's skills to implement the production efficiently. Therefore, we can express G as:

$$G = G(MHC, LHC, X_1) \tag{2.3}$$

In equation (2.3), MHC and LHC are therefore the human capital of firm's leadership and general labor force, respectively. X_1 is a bunch of firm-level controls.

Technology T depends on firm's absorptive capacity of R&D propensity, innovation ability and technology spillovers. It is created and developed as a byproduct of manufacturing operation (Audretsch and Belitski, 2020).[2] Higher efficiency smooths the innovation process, so leading to a higher technology. Therefore, T can be expressed as a function of efficiency G and other constraints X_2:

$$T = T(G, X_2) \tag{2.4}$$

To summarize, we plug equation (2.3) and (2.4) into (2.2), and organize it as:

$$TFP = A(MHC, X, v) \tag{2.5}$$

where X refers to all other influencing factors except managerial human capital, including firm characteristics, financial condition, labor force human capital, market condition, etc.

In equation (2.5), MHC is unobservable and aggregated, so we need to identify whose human capital are included. CEO plays important roles in making decision, leading and coordinating teamwork, monitoring and controlling operation process. Top management team (TMT) supports the decision-making and implements the strategical plans.[3] Due to their important duties, both CEO and TMT's human capital should be considered as the influencing factors of TFP.

To further discuss how MHC aggregates, we first consider individual's managerial human capital of CEO and each TMT member, which has additive impact on TFP. CEO's leadership, managerial skills, and resource absorption all contribute to TFP. TMT members' managerial capacity and collaboration skills also have the similar impacts.

[2] Many papers argue that technology progress is also motivated by operational inefficiency. The operation condition influences absorbing capacity via resource integration and R&D promotion.

[3] Top management team includes CEO, CFO, COO, CTO, and others higher than vice manager position.

Therefore, we start with the formation of individual human capital, expressed as:

$$hc_t = f(e_t, l_t, x_t) \tag{2.6}$$

$f(.)$ is a Mincer Equation in general form.[4] Individual's human capital mainly accumulates via formal education e_t and learning-by-doing l_t. x_t represents one's demographic characteristics, which also captures the aging effect of human capital depreciation. In most cases, x_t and e_t are only the secondary considerations in appointing the leadership, and both of them seem to be fixed by the time of entering workforce. Therefore, their impacts on TFP are limited.

In contrast, human capital gained via learning-by-doing l_t is more important in leadership selection, which is unobserved (Fitzsimmons and Callan, 2016). In the original Mincer Equation, it is measured by the years of experiences in the industry for the labor force. However, for top managers, due to their roles of decision-making and implementation in daily operation, years of working experiences are not sufficient to capture some specific human capital factors, such as managerial skills and coordinating ability. Instead, they can be better measured by various types of job tasks w_t, occupation experiences o_t, and some special experiences s_t:[5]

$$l_t = g(o_t, w_t, s_t) \tag{2.7}$$

Due to a limited information on job tasks, individuals' previous occupations are the reasonable alternative measures of their human capital accumulation via learning-by-doing. It can be expressed as:

$$o_t = o(o^1, \ldots, o^k; ot^1, \ldots, ot^k) \tag{2.8}$$

[4] Many papers assume a linear form of Mincer Equation. We provide a general equation here to make the exposition and explanation clear, while assuming it is linear in the empirical model.

[5] Special experiences include, but not limit to, overseas experiences, government and so on.

where o^i $(i = 1, \dots, k)$ is each occupation experience, and ot^i is its corresponding length.

To sum up, we integrate and rewrite the individual human capital equation (2.6) as:

$$hc_t = f[e_t, x_t, w_t, s_t, o(o^1, \dots, o^k; ot^1, \dots, ot^k)] \tag{2.9}$$

Due to the additive impact of individual's human capital, the collection of CEO and TMT member's diversified experiences widens the spectrum of firm's managerial human capital. Besides this additive impact, the collaboration among team members influences the management efficiency. In this case, experience heterogeneity may also result in coordination inefficiency due to diversified managerial goals and styles. Since team interaction and coordination are relatively complicated and firm-specific, we use the team composition in each human capital characteristic as the proxies, including age, gender, tenure, etc.

Based on above analysis, the composited managerial human capital is expressed as:

$$MHC = H(CEO, TMT) \tag{2.10}$$

$CEO = hc_t^{ceo}$ is CEO's personal human capital. $TMT = [hc_t^{add}, hc_t^{int}]$ is TMT's composited human capital, including additive human capital of each member hc_t^{add}, and the coordination or interaction effect measured by the team composition hc_t^{int}.

In the next section, we discuss which experiences of CEO and TMT play important roles in shifting TFP, as well as their influencing mechanism. Moreover, how to use team composition to measure team's coordination efficiency will also be discussed.

2.3 Data Resources and Variables Selection

We include publicly listed manufacturing firms in China as the original sample, covering the period 2008-2016.[6] We use the main data source the China Stock Market and

[6] TFP is more crucial for manufacturing industry, so we focus on manufacturing firms listed in the main board (A shares), SME board (Small and Medium Enterprises) and GEM board (Growth Enterprises Market).

Accounting Research Database (CSMAR) to get the information of firm and leadership's traits. To estimate TFP, the information to calculate the intermediate cost comes from the Resset database. The info of price index deflators is sourced by the National Bureau of Statistics in China.

The original database contains 12,591 firm-year observations for 1,937 firms. Among these samples, we drop the extreme-sized firms with average number of employees less than 300 or more than 100,000 during 2008-2016, because they potentially have different production and operation modes with other normal-sized firms. After data cleaning, the unbalanced panel data set includes 11,236 firm-year observations for 1,742 firms covering the years of 2008-2016.[7]

In this section, we introduce how to measure the managerial human capital and firm-level controls by using specific proxies. The dependent variable (TFP) cannot be measured directly, so we introduce its estimation strategy in detail in the next section.

2.3.1 Measures of CEO and TMT's Human Capital

For CEO's general experiences, education attainment reflects one's cognitive ability and knowledge reserve. With higher education, CEO has higher management flexibility and stronger innovation capacity (Wiersema and Bantel, 1992; King et al., 2016). Human capital gained via general industrial experiences is more valuable in practical sense, including social skills, cognitive ability and so on. Leadership tenure reflects CEO's familiarity and sensitivity toward firm's condition, problems, and threats. Longer tenure also indicates a broader and deeper connection with collogues, implying better collaboration and larger control power (Shen, 2003). However, it also leads to consistent management strategies, reducing the operation vitality (Miller, 1991).

Overseas experience can be viewed as a proxy for one's resource possession (Conyon et al., 2019). Overseas CEOs get more exposure to advanced management system from

[7] The information of CEO and TMT starts to be collected in 2008 with too many missing records after the year 2017, so we choose the 2008-2017 time window.

abroad.[8] They also possess broader social tie to enlarge spillovers, cooperation opportunity, and resource pool. Moreover, the creative mindset fostered by culture difference leads to flexible management and active innovation. However, overseas CEOs face the adjustment problem when transplanting managerial skills and resources gained from abroad into Chinese industry.

Career experiences in various functions better capture CEOs' human capital in a sense of management.[9] Based on Upper Echelon theory, CEOs with the throughput experiences (finance, accounting, production, etc.) focus more on efficiency improvement rather than product R&D to maintain the sustainable growth due to limited energy and resources. Production CEOs are more familiar with production process, so have higher incentive and stronger ability to conduct process management. Finance/accounting CEOs potentially possess more financial resources and tend to take financial strategies rather than innovation due to task familiarity. With higher efficiency and lower technology, the overall impact of production or finance/accounting CEO is ambiguous.

In contrast, to seek a long-run expansion, CEOs with the output experiences (marketing, R&D, etc.) prefer to take the technology innovation (Hambrick and Mason, 1984). Marketing CEOs have better knowledge of the market needs and firm's own products, thus having higher incentives and capacity to innovate or invent new products. Innovative CEOs have better perspective towards innovation, so they not only value the importance of R&D, but also have higher sensitivity and capacity of selecting and conducting R&D projects. Innovative CEOs also accumulate richer R&D resources via past working experiences.

Based on statistics, around 82% of the CEOs hold bachelor or higher degree with upward trend during 2008-2016 (Table 2.1, Panel A). Average length of general experience and leadership tenure also grew gradually.[10] For CEO's special experiences, almost all of

[8] Though lacking the information on "in which country CEO got overseas experience", we expect that most overseas experiences are gotten from the developed counties with advanced managerial technique.

[9] There are nine functional experiences in the CSMAR database. We combine the design or R&D (innovation), as well as the finance and accounting due to task similarity. We ignore HR, law and management, because extreme proportion of CEOs possess these experiences, leading to identification issue.

[10] Tenure as leader means serving at TMT, board of directors or board of supervisor. We choose the

Table 2.1: Definition and Descriptive Statistics of CEO and TMT Factors

Variable Name	Definition	2008	2012	2016
Panel A: CEO Experiences				
Gen_exp	Years of working experiences (= age - year of education - 6*)	23.96 (6.82)	25.45 (7.05)	27.26 (7.13)
Tenure	Years served in the leadership team* at current firm.	2.24 (1.58)	4.39 (2.46)	5.11 (3.54)
Education_ceo	=1 if CEO holds a bachelor or higher degree.	0.8100 (0.3926)	0.8097 (0.3927)	0.8469 (0.3602)
Oversea	=1 if CEO has industrial or educational oversea experiences.	0.0307 (0.1726)	0.1479 (0.3551)	0.1698 (0.3755)
Production	=1 if CEO has the production experiences.	0.1088 (0.3116)	0.1479 (0.3551)	0.1698 (0.3755)
Marketing	=1 if CEO has the marketing experience in the industry.	0.1158 (0.3202)	0.2180 (0.4130)	0.2932 (0.4553)
Fin_acc	=1 if CEO has either finance or accounting experiences.	0.1046 (0.3063)	0.1364 (0.3434)	0.1698 (0.3755)
Innovation	=1 if CEO has the innovation experience in the industry.	0.1646 (0.3711)	0.2492 (0.4327)	0.2972 (0.4572)
Panel B: TMT Characteristics				
Age_div	The coefficient of correlation of TMT members' age.	9.27 (7.14)	8.89 (5.38)	8.87 (5.09)
Gender	The percentage of female team members.	11.86 (14.27)	14.45 (15.15)	15.66 (15.63)
Education_tmt	The percentage of members with bachelor or higher degree.	74.96 (29.09)	77.40 (25.61)	80.88 (23.38)
Tenure_div	The coefficient of variation of the tenure among TMT members.	0.535 (0.408)	0.524 (0.277)	0.540 (0.111)

* Year of education: Ph.D – 23; Master - 18; Bachelor – 16; Some college – 15; Others – 12;
* Leadership team includes top management team, board of directors, board of supervisors.

them have the upward trends (Figure 2.1 and 2.2). Overseas CEOs increased notably from 3.2% to 8.6% during 2008-2016, though the magnitude is small. With large magnitudes and rapid speed, marketing CEOs raised from 18.3% to 29.3% and innovation CEOs increased from 22.5% to 29.7%. The proportion of finance/accounting CEOs is relatively smaller but grew rapidly from 10.8% to 17%. Production CEO raised from 13% to 17% with smaller magnitude and slow speed .

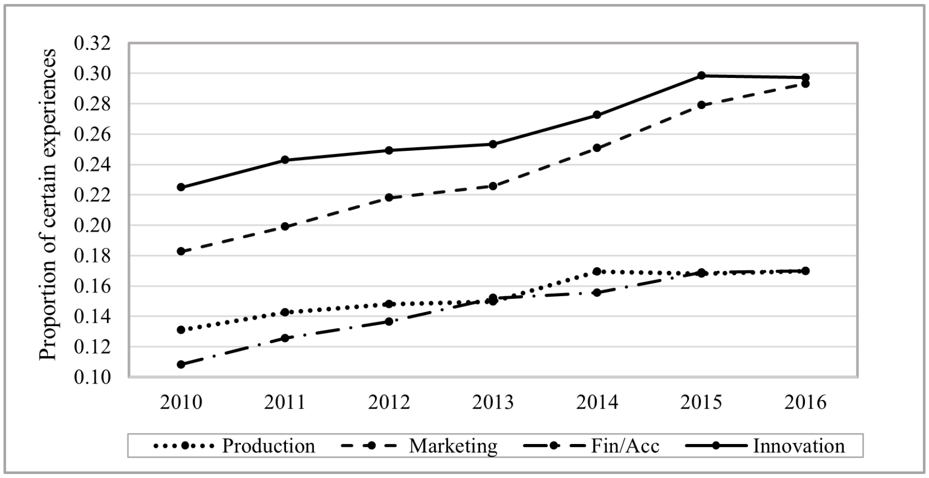


Figure 2.1: Time trends of career experience in various functions

Figure 2.2: Time trends of overseas experience and total number of career experiences

longest one if one takes multiple positions. The reasons include: (1) We only have the info of tenure in leadership position, no info on other positions; (2) General position does not provide as many managerial experiences as in the leadership team.

We analyze the time patterns of CEOs' special experiences for exiting and newly listed firms separately.[11] The trends for newly entered firms are unclear, while the upward trends of existing firms are almost parallel to those of the entire samples.[12] These patterns imply that the importance of overseas and specific industrial backgrounds is gradually realized as the need of globalization. Besides each of these functional experiences solely, the total number of them also has a distinctive impact on TFP. In 2008, CEOs with only one functional experience account for 59.3%, decreasing rapidly to 31.2% in 2016. In contrast, CEOs with 2, 3 and 4 experiences all increased steadily, implying a growing attention paid to the diversity of CEO's backgrounds. To avoid the multicollinearity between each functional experience and their total number, we do not include the latter in the model, but its importance cannot be neglected.[13]

For TMT's factors, executives' education level has similar impact as that of CEO's education. As to gender composition, females potentially bring in different mindsets and managerial styles to correct information biases in operation (Dewatripont et al., 1999). They are also more patient and better at communication, which not only helps smooth the operation by reducing collaboration frictions (Liu et al., 2014), but also widens team's human capital spectrum by accelerating experience exchange among members (Adams and Ferreira, 2009). Finally, females face implicit barrier to climb the career ladder due to "glass ceiling", so they have stronger skills and determination compared to male peers in similar positions (Arfken, et al., 2004).

TMT's age heterogeneity has bivariate impacts. On the one hand, members in different ages have different mindsets, cognitive functions, and attitudes towards operation. Therefore, gender diversity promotes team creativity, thus encouraging innovation and boosting managerial vitality (Miller and Triana, 2009). However, on the other hand, age diversity

[11] We use moving average to show time trend of existing firms by taking the average of last three years (current, last one and last two years) to indicate the proportion of existing firms with certain CEOs.

[12] The unclear trends for newly entered firms might be due to the strong IPO regulation in 2012–2014.

[13] Though we only include 6 out of total 9 experiences, other three have extreme values (HR and Law have lower than 1%, management has larger than 99%), so the level of collinearity should be very high.

leads to collaboration friction, different managerial styles, and poor team integration, resulting in lacking cohesion as the bi-products (Amason, 1996; Miller et al., 1998).

Tenure diversity measures the length of collaboration as executives in current firm. Shorter period of collaboration leads to low operation efficiency due to higher communication costs and larger conflicts (Bernile et al., 2018). Junior and senior members have different opinions towards firm conditions, so they prefer different operation strategies and styles. Though diversified ideas will lead to adjustment problem, they also boost management vitality. Junior members may bring in new ideas and fresh mind, viewing firm's operation from a new angle.

Based on the descriptive statistics, the proportion of female members increased from 11.5% to 15.5% during sample period, and that of bachelor's or higher degree executives also raises from 77% to 81.5% (Table 2.1, Panel B). Though the average age and tenure length both grew gradually during 2008-2016, we do not see the clear time trends for their diversity measures due to the tradeoff between management vitality and smoothness.

2.3.2 Other Firm-level Controls

Firm size is considered in both absolute and relative sense, measured by the number of employees and market share. Absolute size reflects more about firm structure. Larger firms potentially have complex governance structure, leading to lower operation efficiency (Dhawan, 2001). Larger firms also have weaker incentives to make radical changes due to lower risk of bankruptcy. Relative scale reflects firm's interaction with the external market. Firms with larger market share have stronger capacity to attract, integrate, and allocate various resources efficiently, supporting both production and innovation activities.

We also consider firm's financial condition, measured by return to asset (ROA) and debt to asset ratio. More profitable or less financially restricted firms have adequate resources to support various activities, while firms with insufficient funds must give up plans with high uncertainty (Fazzari et al., 1987). Resource shortage also leads to the distortion of resource allocation, and thus reduces both the production efficiency and technology level (Chen and Guariglia, 2013).

Industry cluster in the big cities provides firms with richer resources and larger cooperation opportunity to promote the innovation and production activities. Industry cluster also helps reduce the system costs due to economics of scale and location advantage, including production and transportation expenses. Located in the big cities, firms also have advantage in accelerating the flows of information and resources via industry chain, thus further improving efficiency.

For ownership structure, state-owned firms (SOEs) have higher reputation and policy advantages to attract various resources (Bogart and Chaudhary, 2015). However, they potentially have complex structure and costly operation process/mode which reduce production efficiency. Less threatened by bankruptcy, together with the "social-welfare goal", SOEs also have lower incentives to be profit-driven (Parida and Mandheswaran, 2020).

According to the agency theory, TMT with larger shareholdings has lower dismission pressure, so being more tolerant to the risky investments, such as R&D (Palia and Lichtenberg, 1999). In contrast, executives with fewer shares target more on their own utility and short-run benefits (Coles et al., 2012). Besides motivation, larger shareholdings also imply stronger control power to integrate resources efficiently and respond to shocks quickly.

Based on descriptive statistics, number of employees dropped slightly right after crisis from 2,536 to 2,389, and then recovered to around 3,000 (Table 2.2). Both ROA and debt to asset ratio fluctuated across years without clear time trend. Market share decreased sharply from 0.12 to 0.09 right after the crisis and stayed relatively stable after then. TMT shareholding shows a clear upward trend from 3% to 9.6% during 2008-2016. The proportion of SOEs dropped drastically from 49% to 22.5%, while that of firms located in big cities increased gradually from 22.2% to 26.9%.[14]

[14] General employee's human capital also influences TFP. Unfortunately, we do not have its information (such as the fraction of skilled labor). Since general employees are hired by matching their skills with firm's traits and needs, we assume their human capital is partially explained by firm factors, controlled in our model.

Table 2.2: Definition and Descriptive Statistics of Firm Controls and Dependent Variable

Variables	Definition	2008	2012	2016
ln(TFP)	Estimated TFP with ACF method	1.443 (0.2323)	1.520 (0.2782)	1.605 (0.2076)
Firm_size ($fv1$)	Number of employees (logarithm).	2536 (2152)	2560 (2318)	2957 (3121)
Profitability ($fv2$)	Return to asset ratio (ROA).	0.0207 (0.2231)	0.0414 (0.0929)	0.0471 (0.1872)
Fin_leverage ($fv3$)	Liability to asset ratio.	0.6245 (3.5730)	0.3848 (0.2281)	0.3718 (0.1935)
Market_share ($fv4$)	A firm's annual revenue to total revenue of the "above designed sized firms" in the same industry*;	0.1234 (0.1921)	0.0995 (0.4197)	0.0953 (0.4104)
TMT_share ($fv5$)	The proportion of company shares hold by TMT members.	0.0302 (0.0898)	0.0874 (0.1601)	0.0959 (0.1574)
Big_city ($fc1$)	=1 if the firm is located at big city (Beijing, Shanghai, Guangdong)	0.2218 (0.4157)	0.2570 (0.4372)	0.2689 (0.4435)
SOE ($fc2$)	=1 if the actual controller of the firm is central or local government.	0.4897 (0.5004)	0.2870 (0.4526)	0.2253 (0.4179)

* We also control the financial crisis period. Crisis dummy equals to 1 if year is 2008-2012, and equals to 0 if year is 2013-2016.
* "Above designed sized firms" is defined as the industrial enterprises whose annual operating revenue is at least 20 million RMB based on the new standard approved by China's State Council (2011).

2.4 Estimating Total Factor Productivity (TFP)

We discussed the measures of independent variables and controls in the last section. For the dependent variable TFP, it is unobservable and thus needed to be estimated. We start with the Cobb-Douglas function (2.11) in logarithm form, and then estimate TFP as the residual in the equation (2.12):

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + u_{it} \tag{2.11}$$

$$\widehat{tfp}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \tag{2.12}$$

$y_{it}, k_{it}, l_{it}, m_{it}$ are the output level and three major factor inputs in logarithm form, respectively. ω_{it} is the unobservable TFP and u_{it} is the idiosyncratic error.

Several semi-parametric methods, including Olley-Pakes (OP, 1992), Levinsohn and Petrin (LP, 2003) and Ackerberg-Caves-Frazer (ACF, 2015), are widely used to address the potential endogeneity sourced by the association between input factors and unobservable ω_{it}. The main differences across these methods are endogeneity assumptions on input factors and the proxies selected.[15] In this research, we assume both labor and capital inputs are potentially determined or subject to change after other factors are decided. Therefore, ACF method is used to allow the association between unobservable TFP and above two inputs, with intermediates as the proxy.

In the implementation, as shown in Appendix A.1 Panel A, the number of employees and deflated net fixed assets are adopted to measure the labor input l_{it} and capital stock k_{it}.[16] Without direct measures for intermediates m_{it}, we calculate it based on various operation costs. Deflated annual revenue is adopted as the measure of output y_{it} (Jin, et al.,

[15] OP and LP assume that only capital is endogenous. OP uses investment as proxy, while LP adopts intermediates to avoid "zero-value". ACF assumes both capital and labor are endogenous with intermediates as proxy. Since TFP estimation is not the key to this paper, we do not provide the estimation steps in detail.

[16] Brand-new equipment requires lower maintenance cost with higher efficiency compared to the used ones. Some papers use other strategies to depreciate the fixed assets, such as using a constant industry-specific depreciation rate based on historical data. Due to lacking relevant information, we regard that the net value of fixed assets is a reasonable proxy.

2019). Average annual revenue has an upward trending with moderate turbulence from 1.99 to 2.84 billion RMB during 2008-2016. Capital stock and intermediate inputs increased from 0.74 to 1.24, and 1.69 to 2.18 billion RMB, respectively. Average number of employees is relatively stable across year, between 2,400 and 2,800. These variables show an abnormal pattern during 2009-2012 right after the financial crisis due to the potential change of operation strategies reacting to the external shock.

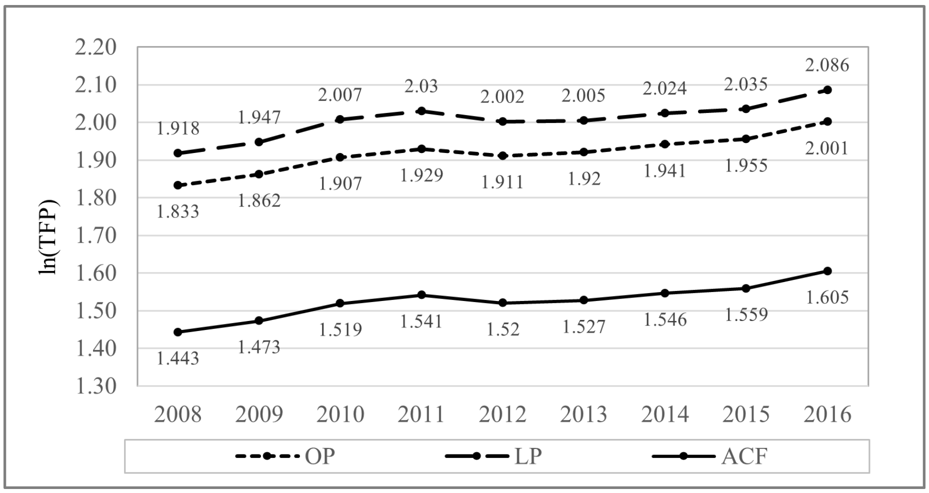


Figure 2.3: Time trends of estimated ln(TFP)

Based on ACF results, the estimate of labor input in logarithm is 0.11, and that of capital and intermediates are 0.05 and 0.84, respectively (Appendix A.1, Panel B).[17] The results imply a major role of intermediates in explaining the productivity for the manufacturing firms, followed by the labor and capital, which are intuitively reasonable. The estimates of all inputs sum up to around one, indicating a constant return to scale for the listed manufacturing firms in China. Shown in Figure 2.3, TFP in logarithm grew gradually during 2008-2016 from 1.44 to 1.61, with fluctuation during 2011-2013 potentially due to IPO regulation. We also estimate TFP with OP and LP methods as the further check. The time trend is consistent across different methods, proved by the evidence that the correlation coefficients between any two are higher than 0.93. Given this extremely strong

[17] We set the replication of bootstrap as 200, which is more than enough for the results to converge. For the model, we assume a fourth polynomial function which has enough orders.

correlation, the results of our empirical work are not expected to vary substantially when TFP_{OP} or TFP_{LP} are employed (Van Beveren, 2012).

2.5 Baseline Specification

Our baseline specification is based on equation (2.5). MHC_{it} includes both CEO and TMT's managerial factors, which are CEO_{it} and TMT_{it}, respectively, referring to a collection of their basic characteristics and past experiences. We assume a linear specification:

$$tfp_{i,t} = \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + \Gamma_t + c_i + \varepsilon_{i,t} \qquad (2.13)$$

Firm-level controls include time-variant factors fv_{it} and invariant variables fc_i.[18] Sub-industry fixed effect is controlled with a set of dummies $DInd_i$.[19] Year dummies are not controlled because they may extract the natural growth of technology from TFP. However, financial crisis dummy is controlled to extract the effect of firm's strategical change in reaction to the market shocks, so the remaining part of TFP change is a pure effect of production capacity growth. We capture the crisis dummy Γ_t by using 2012 as a cutoff according to the patterns of inputs/output in production. c_i is the unobservable heterogeneity and ε_{it} is the idiosyncratic error.

We first adopt pooled OLS estimation as the baseline because it only requires the weakest assumption of contemporaneous exogeneity.[20] It is performed in a stepwise manner. Before we add CEO or TMT variables into the model, R-square shows that only around 9.7% of the TFP variation is explained by the firm controls. Column 1-3 in Table 2.3 represent regression models where CEO and TMT factors are added. We find that

[18] Current TFP depends on firm's traits at current period and financial condition (ROA / asset structure) in the previous period. Taking one period lagged financial condition also helps avoid the potential reverse or simultaneous causality.

[19] Manufacturing has 29 categories based on the National Standard of Industry Classification. We manually re-classify all firms into 10 sub-categories based on similarity to avoid over-control and collinearity. The details of sub-industry classification are in Appendix A.4, based on the two-digit code of the SIC.

[20] Contemporaneous exogeneity only requires the explanatory variables to be independent from the composited error term in the same period, not necessarily in the future or previous periods.

Table 2.3: Pooled OLS, Random Effect and Fixed Effect

	Pooled OLS			RE	FE
	(1)	(2)	(3)	(4)	(5)
A. CEO Experiences					
$Gen\_exp_{i,t}$	0.0013***		0.0011**	0.0013**	0.0013*
	(0.0005)		(0.0005)	(0.0005)	(0.0007)
$Tenure_{i,t}$	-0.0019		-0.0017	-0.0032***	-0.0035***
	(0.0012)		(0.0011)	(0.0011)	(0.0013)
$Education\_ceo_{i,t}$	0.0146*		0.0024	0.0044	0.0202
	(0.0080)		(0.0099)	(0.0109)	(0.0151)
$Oversea_{i,t}$	0.0345***		0.0309***	0.0280**	0.0007
	(0.0084)		(0.0083)	(0.0129)	(0.0199)
$Production_{i,t}$	-0.0358***		-0.0341***	-0.0208**	0.0197
	(0.0080)		(0.0080)	(0.0094)	(0.0138)
$Fin\_acc_{i,t}$	-0.0065		-0.0080	-0.0083	0.0042
	(0.0095)		(0.0095)	(0.0094)	(0.0127)
$Marketing_{i,t}$	0.0051		0.0040	0.0070	0.0174
	(0.0069)		(0.0069)	(0.0081)	(0.0116)
$Innovation_{i,t}$	0.0190***		0.0182***	0.0171**	0.0129
	(0.0066)		(0.0066)	(0.0080)	(0.0120)
B. TMT Characteristics and Experiences					
$Age\_div_{i,t}$		-0.0034***	-0.0024**	-0.0022***	-0.0015**
		(0.0011)	(0.0011)	(0.0005)	(0.0007)
$Gender_{i,t}$		0.0832***	0.0723***	0.0912***	0.0895**
		(0.0210)	(0.0198)	(0.0226)	(0.0348)
$Education\_tmt_{i,t}$		0.0667***	0.0427***	0.0415**	0.0290
		(0.0128)	(0.0157)	(0.0181)	(0.0275)
$Tenure\_div_{i,t}$		-0.0380***	-0.0208**	-0.0199**	-0.0039
		(0.0104)	(0.0102)	(0.0090)	(0.0095)
Observation	6544	7479	6542	6542	6542
R_square	0.1768	0.1130	0.1832		0.0452
Sub-Industry FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

* The significance level: ***0.01, **0.05, *0.1.

* We hind the estimation results for firm-level controls. They are consistent with previous literature.

CEO's experiences explain around 8% of the TFP variation. The magnitude of R-square is almost doubled after controlling both CEO and TMT factors. 18.3% of the TFP variation is explained, implying that leadership's human capital plays important role in shifting TFP.

For CEO's past experiences, length of working experiences significantly raises TFP by 1.3% for every ten more years in the industry. CEO's leadership tenure and formal education have insignificant impacts on TFP with small magnitudes. Overseas and innovation experiences significantly increase TFP by around 3.5% and 1.9% respectively, while production experience hinders TFP by around 3.6%. Finance/accounting experience has negative but insignificant effect on TFP, while marketing experience promotes TFP though this impact is also insignificant. After controlling TMT's factors, the impacts of above-mentioned CEO factors are relatively consistent only with marginal changes in magnitudes.

For TMT factors, every 10% more female members promote a firm's TFP by around 0.8%. Members' formal education also spurs the actual productivity that TFP increases by around 0.7% for every 10% more members with a bachelor's or higher degree. The length of collaboration, measured by tenure heterogeneity, impedes TFP. Both types of team diversity, which are age and tenure, significantly reduce TFP. Every 10% increase of the standard deviation in tenure or age compared to their mean levels reduce TFP by 0.38% and 0.03%, respectively. The impacts of above TMT factors are robust after controlling CEO factors, with marginal magnitude change.

The estimates of firm controls are relatively consistent with literature using Chinese data (Chen and Guariglia, 2013). 10% expansion on firm size reduces TFP by around 0.5%, but it is insignificant. Every 1% increase of ROA and market share promotes TFP by around 0.5% and 0.1%, respectively. 1% higher liability to asset ratio results in 0.26% lower TFP. Every 1% more shares hold by TMT members promote TFP by 1%. State ownership has an ambiguous impact on TFP due to the potential net effect. The firms located at big cities have 4.0% higher TFP on average compared to those who located at developing regions.

Taking the advantages of panel data, we further adopt the Random Effect (RE) method.

It helps improve the efficiency at the cost of a much stronger assumption, which is strict exogeneity. The results are relatively consistent with those in Pooled OLS with marginal changes in magnitudes (Table 2.3, Column 4). 10 more years of general experience significantly promote TFP by 1.3%, while TFP would be reduced by 3.2% for every 10 years longer leadership tenure. Overseas and innovation experiences significantly increase TFP by 2.8% and 1.7% respectively, while production experience impedes TFP by 2.1%.

For TMT factors, 10% more female members promote TFP by around 0.9%. Education level is also positively associated with the TFP that 10% more members with a bachelor's or higher degree increase TFP by 0.4%. Members' tenure and age heterogeneity both impede the productivity to some extent due to the collaboration friction, reducing the TFP by around 0.02% and 0.2% respectively for every 10% increase, which is statistically significant. The results of Pooled OLS and Random Effect support each other, telling a consistent story.

2.6 Endogenous Process of CEO Appointment

Hausman test implies that the endogeneity issue exists. The CEO appointment process is a matching of CEO's human capital to firm's objective conditions and holistic plan. Therefore, CEO's characteristics and past experiences are potentially associated with the unobservable heterogeneity c_i. In contrast, though the CEO turnover rate might be higher after sudden external shocks, due to the time-consuming nature of making and processing dismission decision, CEO turnover does not happen immediately. Therefore, we assume CEO factors are independent from idiosyncratic error at current period, which is ε_{it}.

In making CEO appointment decision, CEO's special experiences are more likely to be considered, while the general experiences are the secondary concern. For instance, compared to the demographic characteristics or formal education, specific functional experiences gained over one's career life are highly valued by the decision-makers. Though CEO's general working length and education are also considered, they only remotely influence the appointment. Therefore, we assume that overseas background and four industrial functional experiences are endogenous, and working length and education are exogenous.

As to empirical methods, the widely used ways to address the endogeneity with panel data is the fixed effect (FE) or first differencing (FD). We first do the within estimation by controlling firm's fixed effect. Results provide some useful information on the frequently changing variables (Table 2.3, Column 5). The length of general working experiences and leadership tenure both have significant impacts on TFP but in opposite directions. For TMT factors, age diversity negatively influences TFP, while larger proportion of females in TMT leads to higher TFP. Above CEO and TMT factors all have consistent results with those in the pooled OLS and RE estimation in terms of directions and magnitudes.

However, the estimates of CEO's special experiences provided by the within-estimation are insignificant or even have the opposite signs compared to those in the pooled OLS and RE. One possible reason is that these experiences, including overseas and four career experiences, are all measured by dummy variables, so they rarely change overtime.[21] In this case, these variables may lack enough within variation after taking time-demean or first-difference, leading to inefficient or even inconsistent estimates. To provide supplement results to remedy the potential weakness of within FE, we adopt the alternative methods of Pooled 2SLS and Random-Effect Instrument Variable (RE-IV) to get rid of doing time-demean or first-difference.

To implement RE-IV, we first adopt the Hausman-Taylor method to seek instruments from within the panel system. These internal IV candidates include demeaned time-variant variables $z_1 = [\ddot{TMT}_{i,t}, \ddot{fv}_{i,t}]$, as well as the non-redundant exogenous time-variant variables at all periods $z_2 = [TMT_{i,s}, fv_{i,s}]$ $(s \neq t)$. Although these internal IVs technically satisfy the IV assumptions, some of them are weak instruments due to remote relation with CEO assignment. Appointment decision is usually made by the board of directors after considering firm's objective conditions, together with the opinions from board of

[21] Though we find an upward trending for CEO's special experiences, the change rate is small. Only when firm replaces its CEO, these variables have the chance to change, but they are also not necessarily to change.

shareholders. Therefore, TMT factors are only weakly related to CEO appointment, so we eliminate TMT-related instruments. Time-demeaned factors, $\ddot{fv}_{i,t}$, imply firm's turbulence in specific period, which might be the source of CEO turnover.[22] Among these time-demeaned instruments, the fluctuation of financial condition in the short run will not lead to the change of CEO immediately, but the structural change may indicate the potential personnel change. In this case, we choose time-demeaned firm size and market share due to their close association with CEO turnover, so $IV_1 = [\ddot{fv}1_{i,t}, \ddot{fv}3_{i,t}]$.[23].

However, we have five endogenous variables but only two instruments so far, so we need extra external instruments which are related to CEO's special experiences. As assumed, CEOs in the same industry, same province and at same year may share similar experiences, because these companies have similar preference on CEO selection because of facing similar market, business, local policy, and environment. Therefore, we use the proportion of CEOs in the same industry, province and year with certain experiences as external IVs, $IV_2 = [o_{i,t}, p_{i,t}, f_{i,t}, m_{i,t}, i_{i,t}]$.[24] These instruments are thus closely associated with CEO's specific experience, while independent from the unobserved heterogeneity and random shocks. We therefore have seven instruments for five endogenous variables:

$$IV_s = [IV_1, IV_2] = [\ddot{fv}1_{i,t},\ \ddot{fv}3_{i,t},\ o_{i,t},\ p_{i,t},\ f_{i,t},\ m_{i,t},\ i_{i,t}]$$

The estimation results show that most of CEO factors are still significant in RE-IV method after improving efficiency (Table 2.4, Column 2 and 3).[25] General working length is positively associated with TFP. 10 more years in the industry lead to 2.3% higher TFP. Leadership tenure significantly reduces TFP by 3% for every ten more years as a leader in current firm. This result implies that the negative impact of sluggish management taken by long-tenured CEO overweighs the positive effect of CEO's familiarity to operational

[22] We drop z_2, which are the level of firm factors at all other periods. They are more likely related to firm factors at current period, so they potentially violate the exclusion assumption, being weak IV.

[23] The detailed notation is in Table 2.2

[24] $o_{i,t}, p_{i,t}, f_{i,t}, m_{i,t}, i_{i,t}$ are instruments for overseas, production, fin/acc, marketing and innovation experiences, respectively. More details are explained in Appendix A.2.

[25] The first-stage regression results are attached in Appendix A.3.

Table 2.4: Pooled 2SLS, RE-IV and Dynamic Perspective

	Pooled 2SLS	Baseline RE-IV		Dynamic RE-IV	
	(1)	(2)	(3)	(4)	(5)
$\ln(TFP)_{i,t-1}$				0.3378***	0.3274***
				(0.0249)	(0.0247)
A. CEO Experiences					
$Gen\_exp_{i,t}$	0.0014***	0.0023***	0.0021***	0.0016***	0.0015***
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
$Tenure_{i,t}$	-0.0011	-0.0030**	-0.0029**	0.0003	0.0006
	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0011)
$Education\_ceo_{i,t}$	0.0056	0.0058	0.0004	0.0094	0.0123
	(0.0111)	(0.0109)	(0.0120)	(0.0091)	(0.0105)
$Oversea_{i,t}$	0.0183	0.1191***	0.1070***	0.0821***	0.0730***
	(0.0251)	(0.0382)	(0.0380)	(0.0278)	(0.0278)
$Production_{i,t}$	-0.0361	-0.0699***	-0.0656***	-0.0729***	-0.0673***
	(0.0307)	(0.0251)	(0.0247)	(0.0212)	(0.0209)
$Fin\_acc_{i,t}$	-0.0468*	-0.0424*	-0.0475**	-0.0555***	-0.0584***
	(0.0281)	(0.0231)	(0.0231)	(0.0187)	(0.0187)
$Marketing_{i,t}$	0.0520**	0.0661***	0.0624***	0.0642***	0.0633***
	(0.0263)	(0.0231)	(0.0230)	(0.0199)	(0.0199)
$Innovation_{i,t}$	0.0220	0.0806***	0.0727***	0.0265	0.0222
	(0.0265)	(0.0235)	(0.0233)	(0.0209)	(0.0206)
B. TMT Characteristics and Experiences					
$Age\_div_{i,t}$	-0.0024**		-0.0020***		-0.0016***
	(0.0011)		(0.0006)		(0.0005)
$Gender_{i,t}$	0.0777***		0.0906***		0.0632***
	(0.0198)		(0.0241)		(0.0192)
$Education\_tmt_{i,t}$	0.0421**		0.0274		-0.0017
	(0.0165)		(0.0193)		(0.0163)
$Tenure\_div_{i,t}$	-0.0189*		-0.0164*		0.0002
	(0.0100)		(0.0091)		(0.0099)
Constant	1.5945***	1.5594***	1.5535***	0.9817***	0.9981***
	(0.0459)	(0.0427)	(0.0444)	(0.0534)	(0.0545)
Observation	6542	6544	6542	5058	5057
Industry FE	Y	Y	Y	Y	Y
Firm-level Controls	Y	Y	Y	Y	Y

* The significance level: ***0.01, **0.05, *0.1.

condition. CEO education has insignificant impact on TFP. In general, CEOs with higher degree have broader horizon and stronger managerial skills, promoting operation efficiency and technology progress. However, these advantages are major-specific. Some education specialties have positive impacts on TFP, such as science/engineering, while others have negative or no association, such as legal degree (Barker and Mueller, 2002). Therefore, there is no significant association at conventional level.[26]

CEO's overseas experience significantly facilitates TFP by 11.9% as a potential result of better perspectives towards innovation and stronger managerial ability. Production or finance/accounting CEO significantly hinders TFP by 7% and 4.2%, respectively, due to a dominant effect of lower innovation incentives. Marketing or innovation CEO raises TFP by around 6.6% and 8.1%, respectively, as the potential result of better perspectives and more information towards market demand and products, as well as a more flexible management style. The impact of CEO's special experiences on TFP is still significant after controlling for the TMT factors.

For TMT composition, every 10% more female members lead to around 0.9% higher TFP due to diversified management ideas, smooth communication, and efficient collaboration in the workplace. 10% more well-educated members promote TFP by around 0.4% due to broader horizon and better perspectives towards operation and strategical design, as well as stronger management skills. Tenure and age diversity significantly impedes TFP by 0.2% and 1.9% respectively for every unit increase in coefficient of variation. Age diversity reflects different styles and opinions toward management, boosting managerial vitality by bringing in new ideas on the one hand, but leading to communication friction on the other. Smaller tenure diversity reflects longer cooperation length among members, which implies better coordination and less conflicts but leads to the "sluggish management" with rigid strategies as the bi-product. For these two diversity variables, although they influence TFP in both directions, the negative direction seems the dominant one.

[26] Barker and Mueller found insignificant association between conventional education level and R&D spending which is one of the sources of technology progress and thus TFP promotion.

The results of endogeneity-adjusted estimation are quite consistent with those in the baseline estimation. Though we find the marginal change in significance and magnitudes, the directions of the estimates are the same. CEO's marketing and finance/accounting experiences become significant, with the same signs and larger magnitudes. One possibility is that, due to the potential association, the pure impacts of CEO's experiences are partially soaked up by the unobserved heterogeneity, losing the explanation power. In all, these two methods tell a consistent story.

2.7 The Long-run Effect of Managerial Human Capital

We then consider a dynamic specification to see the long-run effect of CEO and TMT's human capital. Given the continuity of firm's operation, TFP at current period may depend on its past value, showing a state dependence, so we add the one-period lagged TFP into equation (2.13) to control its persistent trend or serial correlation.[27] Moreover, the regressors might also have the lasting effects on TFP. Due to the inclusion of more lagged periods of independent variables and controls, lagged TFP helps to mitigate the omitted variable bias at the meantime.[28] However, the inclusion of lagged CEO and TMT factors may cause high level multicollinearity, because they are potentially associated with managerial factors at current period according to the rarely changing nature. In this case, dynamic specification tells us a story of the long-run effect, giving us a supplement of static specification.

The AR(1)-type dynamic model is then constructed as:

$$tfp_{i,t} = \gamma \cdot tfp_{i,t-1} + \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + \Gamma_t + c_i + \varepsilon_{i,t} \quad (2.14)$$

In equation (2.14), $tfp_{i,t-1}$ is endogenous due to its inclusion of c_i. In the firm- or household- level research, the widely used ways to address this issue is the IV estimation (or Pooled 2SLS) suggested by Anderson and Hsiao (1981), and the IV-GMM method

[27] Based on exiting papers and test results, one-period lag is enough to control the persistent effect.

[28] We do not know how many periods of lagged factors have significant effects on TFP. Therefore, we directly control $tfp_{i,t-1}$ to include the independent variables and controls in all past periods.

proposed by Arellano and Bond (1991). Both methods deal with the association between firm's unobserved heterogeneity and endogenous variables by taking first-difference on equation (2.14) to remove c_i, and select appropriate instruments for the new endogenous variable $\Delta tfp_{i,t-1}$.[29] However, a similar issue exists that CEO dummies lack enough within variation after differencing the original equation. Moreover, the differencing operation also magnifies the gaps in a case of unbalanced panels.

Arellano and Bover (1995) / Blundell and Bond (1998) thus introduced a system-GMM method to address this issue. Instead of transforming equation (2.14), they do first-difference on the instruments, making them exogenous to c_i, meaning that using $\Delta tfp_{i,t-1}$ as the IV for $tfp_{i,t-1}$. It is proved to be a valid IV, because $corr\ (\Delta tfp_{i,t-1}, tfp_{i,t-1}) \neq 0$ and $corr\ (\Delta tfp_{i,t-1}, v_{i,t}) = 0$ (Appendix A.2). However, this method assumes all available instruments come within the panel system, while the inclusion of external instruments is not allowed. In our case, though these internal IV satisfy the basic assumptions theoretically, they might be weak instruments because they are remotely associated with the endogenous variables.

To overcome these weaknesses, we take an alternative strategy by extending the RE-IV setup in the last section. To implement, we keep all instruments in the static model, and inspired by the system-GMM to select one more IV for the extra endogenous variable $tfp_{i,t-1}$, which is $\Delta tfp_{i,t-1}$.[30] Using this strategy, we not only get consistent estimates, but also keep a consistent implementation with the static specification. The instruments used in dynamic model thus are:

$$IV_d = [\Delta tfp_{i,t},\ \ddot{fv1}_{i,t},\ \ddot{fv3}_{i,t},\ o_{i,t},\ p_{i,t},\ f_{i,t},\ m_{i,t},\ i_{i,t}]$$

Based on the results, TFP in the last year explains a firm's current productivity to a large extent with an estimate around 0.33 (Table 2.4, Column 4 and 5). $\hat{\gamma} < 1$ implies that

[29] Anderson-Hsiao uses $y_{i,t-2}$ as an instrument for $\Delta y_{i,t-1}$, while Arellano-Bond further derives all relevant moment conditions to improve the efficiency, using $[y_{i,t-2}, y_{i,t-3}, \ldots, y_{i,1}]$ as instruments for $\Delta y_{i,t-1}$.

[30] Though even earlier lagged difference can also be IVs, some papers point out that they lead to bias in finite sample case. Moreover, we need to manually do this estimation at a cost of losing sample size.

current TFP has a depreciation effect on future TFP level.

After controlling for lagged TFP, the impacts of CEO's experiences are consistent with those in the static specification. CEO with ten more years of general working experience significantly raises TFP by 1.5%, while tenure length insignificant affects TFP due to a potential offset effect of stronger control power and inertia management. The impact of CEO's education is also insignificant after controlling for other experiences. CEO with overseas, marketing, or innovation experience promotes TFP by around 7.3%, 6.3% and 2.2%, respectively, due to larger operation flexibility and higher innovation motivation. Production or finance/accounting experience still significantly hinders TFP by 6.7% and 5.8%, respectively.

To see the long-run impacts, CEO with overseas, marketing or innovation experience leads to an accumulated 10.9%, 9.4%, and 3.3% respectively in a long-run perspective, compared to those firms whose CEOs do not have these corresponding experiences. In contrast, CEO with production or finance/accounting experience significantly reduces TFP by 10% and 8.7% respectively in the long run. The accumulative long-run impacts of these special experiences are comparable to 1.5 times the magnitudes in a static view.

For TMT factors, every 10% more female members raise TFP by 0.6% due to a smoother and vital teamwork sourced by diversified ideas and better communication. Members' education has insignificant impact after controlling for other factors. Age diversity impedes TFP significantly by 0.16%, indicating that the negative impact of operation frictions overweighs the advantages of diversified opinions. Tenure heterogeneity has insignificant impact on TFP due to the interaction between richer human capital pool and opinion/style collision. TMT's composition also has the long-run impact on TFP that every 10% more female executives increase TFP by 0.9% in the long run, while the accumulative negative impact of TMT's age diversity on TFP converges to 0.23%.

Comparing the impacts of CEO and TMT factors in static and dynamic specifications, only a small number of CEO factors change their significance after controlling the persistence of TFP trend, such as CEO's tenure and innovation background. As we mentioned, besides the finite sample bias, another possible explanation is the multicollinearity. Lagged TFP is explained by CEO's experiences at lagged periods. Therefore, if a firm does not change its CEO across sequential years, lagged TFP should be highly correlated to current CEO factors to a large extent. Despite this issue, the results in dynamic specification still have the reference value, not only because they further support the basic results in a static view, but also provide a broad picture of CEO and TMT's long-run impacts.

2.8 Sensitivity-test with Detrending Strategy

Due to the panel data nature, all variables have the time-series properties.So far, we assume the TFP growth is a stationary process, meaning that the TFP level at different years have the same distribution, and the relationship between $tfp_{i,t}$ and $tfp_{i,s}$ $(t \neq s)$ does not change across time.[31] However, this assumption is too ideal, and usually violated in the real world cases.

Many economic factors have the growing tendency in time-series. In Section III, we also find that both TFP level and the proportion of CEOs with certain special experience have the similar upward trending. So far, we only verify the potential association between TFP and managerial factors, but cannot tell whether this association is a causal relationship, or only because they are influenced by the same confounding factors (usually the macroeconomic factors), and thus share the similar time-trends.[32] Moreover, in the last section, we find that though the estimated coefficient of $tfp_{i,t-1}$ is around 0.35, and we cannot rule out the possibility of unit root based on test result.

To further address this issue, we do a senstivity test by following a traditional method of time-detrending. Instead of controlling for crisis dummy, we create a time-trend variable with the value equivalent to the number of year, $Trend_t$, to control the nature linear trend

[31] The stationary process implies that TFP at each year has the same data generating process.
[32] These confounding factors include but not limit to the internalization, economy growth, etc..

of TFP, transforming a trend-stationary process to a stationary time-series.[33] Though using this method can address the problem in time-series dimension, it has the efficiency problem. Therefore, we use it as a supportive test for the baseline and dynamic specifications. The setup of time-trend-control specification is as following:

$$tfp_{i,t} = \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + Trend_t + c_i + \varepsilon_{i,t} \qquad (2.15)$$

The result verifies that TFP itself has a nature upward trending, reflected by a positive significant coefficient for time-trend variable (Table 2.5). After controlling for the nature time trend, the impacts of managerial human capital are relatively consistent with those in the baseline model, only having marginal changes in magnitudes. Besides the positive impact of general working experiences and negative effect of leadership tenure, CEO's special experiences still notably influence the TFP promotion. Overseas and innovation experiences promote TFP by around 8% and 5.1%, respectively, while functional experiences in production and finance/accounting hinder TFP by around 7.9% adnd 6.8%, respectively. Their impacts on TFP are all significant in both statistical and economical sense, only having marginal changes compared to those in the baseline model (10.9%, 7.3%, -6.6% and -4.8%, respectively).

For TMT factors, age and tenure diversity negatively hinders TFP by 0.21% and 2.1% for every one unit change in ratio of standard deviation to its mean. Larger proportions of female and highly-educated executives promote TFP, reflected by the evidence that every 10% more females or highly educated members raise TFP by 0.85% and 0.22%, respectively, which are comparable to 0.91% and 0.27% without controlling the time-trend.

Above results further support the story told by the baseline estimation, partially verifying that CEO's experiences and TMT composition have the causal relationship with TFP. We also find an interesting pattern that, after controlling for the time trend, the positive impacts of CEO's overseas experience, innovation background and length of industrial

[33] For instance, at year 2008, the value of this variable is 2008. We do not directly control the year fixed effect, because it potentially leads to overidentification and multicollinearity issue.

Table 2.5: Sensitivity Test with Time-detrending (RE-IV)

	Baseline Specification		Dynamic Specification	
	CEO	CEO\TMT	CEO	CEO\TMT
$\ln(TFP)_{i,t-1}$			0.3313***	0.3209***
			(0.0250)	(0.0247)
Time_trending	0.0138***	0.0136***	0.0109***	0.0108***
	(0.0018)	(0.0018)	(0.0020)	(0.0020)
A. CEO Experiences				
$Gen\_exp_{i,t}$	0.0016***	0.0014**	0.0014***	0.0012**
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
$Tenure_{i,t}$	-0.0051***	-0.0051***	-0.0006	-0.0004
	(0.0012)	(0.0012)	(0.0011)	(0.0011)
$Education\_ceo_{i,t}$	0.0038	-0.0002	0.0093	0.0127
	(0.0108)	(0.0120)	(0.0091)	(0.0105)
$Oversea_{i,t}$	0.0924**	0.0802**	0.0720***	0.0629**
	(0.0383)	(0.0381)	(0.0279)	(0.0278)
$Production_{i,t}$	-0.0814***	-0.0793***	-0.0816***	-0.0773***
	(0.0251)	(0.0247)	(0.0211)	(0.0209)
$Fin\_acc_{i,t}$	-0.0626***	-0.0677***	-0.0643***	-0.0674***
	(0.0233)	(0.0232)	(0.0187)	(0.0187)
$Marketing_{i,t}$	0.0298	0.0266	0.0510**	0.0497**
	(0.0242)	(0.0241)	(0.0203)	(0.0204)
$Innovation_{i,t}$	0.0578**	0.0511**	0.0159	0.0120
	(0.0238)	(0.0236)	(0.0211)	(0.0208)
B. TMT Characteristics and Experiences				
$Age\_div_{i,t}$		-0.0021***		-0.0016***
		(0.0006)		(0.0005)
$Gender_{i,t}$		0.0847***		0.0614***
		(0.0240)		(0.0191)
$Education\_tmt_{i,t}$		0.0221		-0.0034
		(0.0192)		(0.0162)
$Tenure\_div_{i,t}$		-0.0208**		-0.0021
		(0.0091)		(0.0099)
Constant	-26.1309***	-25.8079***	-21.0406***	-20.7308***
	(3.5275)	(3.5224)	(4.0044)	(4.0058)
Observation	6544	6542	5058	5057
Firm Controls	Y	Y	Y	Y
Time-detrending	Y	Y	Y	Y

* The significance level: ***0.01, **0.05, *0.1.

experiences, as well as larger proportions of female and highly-educated TMT members, are all comparatively smaller than those in the baseline. In contrast, the negative impacts of CEO's production experience, finance/accounting background and length of leadership tenure, as well as two kinds of TMT diversity, are all relatively larger than those in the baseline. These patterns prove that TFP itself has the nature growth trend as the result of economic growth, and the association between some ”positive-impact” experiences and TFP is partially explained by the common trend. The common trends also absorb the partial negative impacts of some factors that hinder the TFP.

2.9 Heterogeneous Influencing Channels in Sub-industry

The influencing or formation channels of TFP in different types of firms may differ due to their different structure and production mode. Therefore, we are also interested in investigating the heterogeneous impacts of managerial human capital in different sub-industries. In previous sections, all manufacturing firms are classified into ten sub-industries based on their product and task similarity. However, if we redo estimation for each of these sub-industries or add interaction terms of each CEO/TMT factor with sub-industry dummies, the degree of freedom will not be large enough to guarantee consistent results.

Based on the factor-intensive types on production inputs and product property, we therefore reclassify firms into two categories, tech-intensive and traditional companies. The former refers to those whose main business is tech-intensive products, such as equipment, electronic, automobile, machinery, etc. These firms aim at developing innovative products, which require higher technology in the production (both process and equipment) to support invention, so focusing more on the technology innovation to achieve higher TFP.

The traditional manufacturing firms have their main business in food, beverage, textile, lumber raw material processing, and so on. These companies chase higher quality and larger quantity of production outputs, while pay less attention on new inventions. Therefore, they focus more on the improvement of production and management process to achieve larger TFP via higher efficiency. Based on the descriptive statistics, both categories have enough samples with comparable numbers of firm-year observations, 5,260 and 5,838 for tech-intensive and traditional firms, respectively.

By doing RE-IV on tech-intensive and traditional firms separately, we find that managerial factors have heterogeneous impacts on them (Table 2.6). Compared with traditional firms, CEO and TMT play even more important roles in the high-tech companies. Long-tenured CEO has negative impact on TFP that one more year in the leadership at current firm reduces TFP by around 0.5%. In both static and dynamic views, overseas CEO significantly raises TFP by around 19%, much larger than that in the whole samples (7%-10%).

As to the long-run effect, overseas CEO accumulatively raise TFP by 24% . Production CEO impedes TFP by 8% in static specification, while has an insignificant impact in a dynamic view as a potential result of high-level multicollinearity. The impacts of both finance/accounting and marketing experiences are insignificant, but the magnitudes and directions are comparable to those in the whole samples. Innovation CEO significantly raises TFP by 13% in dynamic specification, with a long-run effect converges to 16%. In contrast, with the whole samples, innovation CEO promotes TFP only by around 2%-7%.

For traditional manufacturing firms, we find different patterns on CEO experiences. In static specification, every 10 more years of general experiences significantly raise TFP by around 2.3%. The impact of leadership tenure length is insignificant in both static and dynamic specifications. Overseas CEO still notably increases TFP by around 12%, with the long-run effect of 14.2%, which are much lower than those of the high-tech firms. For career experiences in various functions, they all have insignificant impacts on TFP with much smaller magnitudes compared to high-tech firms, though the signs are the same.

The impacts of TMT composition also tell different stories between these two types of firms. Age diversity has a positive but insignificant impact in tech-intensive firms, while impedes TFP significantly in the traditional firms by 0.5% with a long-run effect of 0.6%. Larger proportion of female members lead to higher TFP in both tech-intensive and tradi-

Table 2.6: Heterogenous Impacts in Different Sub-industries (RE-IV)

	High-tech Firms		Traditional Firms	
	Baseline	Dynamic	Baseline	Dynamic
$\ln(TFP)_{i,t-1}$		0.1835***		0.1167***
		(0.0334)		(0.0337)
A. CEO Experiences				
$Gen\_exp_{i,t}$	0.0011	0.0001	0.0023**	-0.0002
	(0.0008)	(0.0010)	(0.0009)	(0.0010)
$Tenure_{i,t}$	-0.0049***	-0.0025	-0.0018	-0.0001
	(0.0017)	(0.0018)	(0.0017)	(0.0016)
$Education\_ceo_{i,t}$	-0.0139	-0.0215	0.0004	0.0305*
	(0.0177)	(0.0213)	(0.0165)	(0.0173)
$Oversea_{i,t}$	0.1835***	0.1958***	0.1220**	0.1258**
	(0.0523)	(0.0609)	(0.0551)	(0.0626)
$Production_{i,t}$	-0.0803**	0.0172	-0.0274	0.0233
	(0.0339)	(0.0380)	(0.0357)	(0.0384)
$Fin\_acc_{i,t}$	-0.0506	-0.0635	-0.0177	-0.0395
	(0.0382)	(0.0438)	(0.0288)	(0.0316)
$Marketing_{i,t}$	0.0473	0.0568	0.0404	0.0064
	(0.0346)	(0.0406)	(0.0305)	(0.0334)
$Innovation_{i,t}$	0.1689***	0.1303***	0.0045	-0.0575
	(0.0280)	(0.0331)	(0.0410)	(0.0488)
B. TMT Characteristics and Experiences				
$Age\_div_{i,t}$	0.0003	0.0011	-0.0041***	-0.0053***
	(0.0007)	(0.0008)	(0.0008)	(0.0008)
$Gender_{i,t}$	0.1433***	0.1369***	0.0591*	0.0401
	(0.0334)	(0.0391)	(0.0358)	(0.0391)
$Education\_tmt_{i,t}$	0.0019	0.0191	0.0395	0.0136
	(0.0269)	(0.0320)	(0.0276)	(0.0306)
$Tenure\_div_{i,t}$	-0.0417***	-0.0429***	0.0073	0.0243*
	(0.0127)	(0.0156)	(0.0131)	(0.0134)
Constant	1.5760***	1.1546***	1.6181***	1.5186***
	(0.0567)	(0.0853)	(0.0651)	(0.0957)
Observation	3121	2410	3368	2605
Firm Controls	Y	Y	Y	Y

* The significance level: ***0.01, **0.05, *0.1.

tional firms, while the magnitudes are much larger in the high-tech firms. Every 10% more female executives increase TFP by 1.4% with a long-run effect of 1.7% in the high-tech firms, while only around 0.4% in the traditional sector. Tenure heterogeneity hinders TFP in the tech-intensive firms significantly by 4.3% with a long-run effect of 5.2%.

Results above verify our hypothesis that high-tech and traditional manufacturing firms potentially have different channels to achieve higher productivity. Tech-intensive firms are more sensitive to their leadership, reflected by the evidence that CEO's career experiences in various functions significantly affect TFP, while their impacts in traditional firms are much weaker and insignificant. To discuss in detail, CEO's experiences that reflect innovation and operation vitality (innovation, overseas, etc.) significantly spur TFP in tech-intensive sector, while those experiences that hinder firm's operation vitality and innovation impede TFP (production, longer tenure, etc.). In contrast, in the traditional manufacturing sector, CEO experiences that improve production and operation efficiency promote TFP (general experiences, education, overseas, etc.), while others have weaker impacts. Above results further support that tech-intensive firms have higher requirement of innovation and technology on their products, so creativity and vitality are the priority, while improving process efficiency is the main channel to boost productivity in traditional firms.

2.10 Conclusion

The main goal for the manufacturing firms is to promote input-output conversion rate in production, measured by total factor productivity. To raise it, two major channels are efficiency improvement and technology promotion. Both channels are potentially influenced by leadership to a large extent, due to its neglectable roles in daily operation.

Due to delegation, CEOs play an important role in making decision and leading teamwork. CEOs' unobservable human capital can be better reflected by their past experiences, including the experiences in general and in special functions. Besides the widely discussed factors (length of industrial experiences, education, tenure, etc.), we find that CEO's overseas, marketing and innovation experiences raise TFP by 5%-10% respectively. These special experiences imply the creative mindset, advanced skills, and better perspectives towards market and products, so these CEOs have larger motivation and stronger capacity to pursue innovation and process adjustment. In contrast, CEO with production or finance/accounting experiences reduces TFP by around 4%-7% respectively with a possible explanation of lower incentive in innovation.

Top management team mainly plays a supportive duty in the implementation, so members' aggregated human capital and team collaboration both influence TFP. We find that larger portion of females or well-educated members leads to higher TFP due to the potentially stronger skills in team coordination to improve efficiency. Larger age or tenure diversity imply diversified styles and opinions towards operation, so they boost creativity and managerial vitality on the one hand, while lead to larger collaboration frictions on the other. Our results show that the latter channel is the dominant one in manufacturing sector, reflecting by the negative impacts.

When separately considering the high-tech firms and traditional companies, the impacts of managerial human capital on them are different. In high-tech firms, CEO's special experiences are highly valued, especially those reflecting better sense and skills of innovation, or helping boost management vitality. In contrast, the smoothness of operation to boost productivity is the priority in traditional manufacturing sectors. Therefore, the general experiences in the industry, as well as advanced management skills would contribute more to promote production efficiency.

CHAPTER 3

LEADERSHIP'S HUMAN CAPITAL AND CORPORATE R&D INVESTMENT

3.1 Introduction

As we discussed previously, Chinese manufacturing firms suffer from the severe external condition and intense market competition in recent years, requiring higher TFP to maintain long-run growth. Technology progress is examined as one among the most important channels to boost TFP. Innovation is one strategy that serves as the engine of technology progress, helping firms to maintain the sustainability. As the starting point, R&D investment fosters innovation success, thus playing important role in a firm's sustainable development. Therefore, analyzing the influencing factors and mechanisms of R&D inputs is of great value.

Many papers discuss the R&D decision-making and innovation outcomes in terms of a company's objective conditions and inherent traits, including firm age, size, financial condition, external environments, etc. These factors reflect a firm's operational preference and unique goals, therefore leading to heterogeneous R&D strategies across firms (Cohen and Klepper, 1996; Lee and Sung, 2005; Fan and Wang, 2019). Besides basic traits, financial conditions and operation strategies also affect R&D propensity (Aghion et al., 2012; Howell, 2017). The external conditions, such as competition intensity and market demand, also influence a firm's incentives to innovate (Kamien and Schwartz, 1975; Acs et al., 1987). Moreover, the innovative environment and other supports provided by the government are also negligible, such as the preferable policies, including tax benefits, R&D subsidies and direct investment (Chen et al., 2018).

These papers leave key questions unexplained: why do firms with similar internal/external conditions and basic traits still take different R&D strategies? What factors are omitted in explaining this heterogeneity? To answer these questions, a series of papers further points out that the leadership team also influences R&D activities, because it is responsible for determining the budget plan and adjusting R&D investment in implementation. Existing research argues that the control power, external stimulus, and managerial incentives are the bridge to link the leaders' traits with R&D spending. The agency problem, managerial control power (such as position duality and delegation), and team composition (such as the proportion of independent directors) all contribute to R&D incentives (Overvest and Veldman, 2008; Zona, 2016; Lee et al., 2020).

Though managerial factors are widely discussed, only limited number of papers explore the influencing factors of corporate innovation in the context of managerial human capital. Demographic characteristics and general experiences are adopted to measure the managerial human capital. Age, gender, and tenure of the top management team may all influence R&D investment, explained by the agency theory and upper echelon theory (Chen et al., 2010). Besides demographic characteristics, general experiences of individual decision-maker or team composition are also said to make contribution to innovation propensity, such as that education level, tenure board size, and board meeting frequency (Ann and Minshall, 2012; Chen, 2013).

Some papers also discuss the corporate decision-making from the angle of managerial human capital. Innovative human capital is explained or formed by the formal education, training, willingness to change, and job satisfaction (McGuirk et al., 2015). Relevant topics are also discussed in Chinese context, examining that a firm's general and managerial human capital both affect its innovation outcome in manufacturing sector (Sun et al., 2020).

Besides the basic traits and general experiences, some novel measures are also discussed. CEO's education in some specific fields, such as advanced science or engineering, and some special functional experiences (marketing, finance, technical, etc.), as well as the industrial interlock, all have a prolong impact on R&D incentives (Barker and Mueller, 2002; Dalziel et al., 2011). R&D incentives and performance are also positively influenced by the past management and government experiences (Lin et.al, 2011). Independent directors' past CEO experience in the same industry contributes to firm's value-added via the channel of innovation, while their CEO experience or same industry background itself does not have the significant impacts (Kang et al., 2018). Measured by the option-stock execute behavior and press-based indicator, firms led by overconfident CEOs not only have more vibrant R&D activities but also perform better in innovation (Malmendier and Tate, 2005&2008; Galasso and Simcoe, 2011; Hirshleifer et al., 2012).

This topic especially has the practical implications for the Chinese manufacturing industry. Facing the pressure of rapidly growing production costs in recent years, Chinese manufacturing firms and governments at various levels are focusing heavily on innovation. For instance, the R&D expenditure of China has ranked second in the world since 2013.[1] Enterprises are the main impetus for R&D investment, contributing to 68.5% of the overall R&D growth. Therefore, China's practice of promoting innovation provides useful information for studying R&D behavior at the firm level (Howell, 2016; Che et al., 2018; Chen et al., 2018).

3.2 Theoretical Framework

Based on Crépon, Duguet, and Mairessec (1998), the innovation process consists of several iterative and incremental stages, including R&D inputs, innovation outcomes, and productivity.[2] In this paper, we focus on the input stage because the R&D investment decision is directly determined by the executive leadership.

We first construct a theoretical framework by referring to the model proposed by Campbell et al. (2011). We assume the executive leadership aims to maximize profits under the perfect market competition assumption.[3] Therefore, firms can only adjust their

[1] This and following data come from the R&D Investment Report of National Bureau of Statistics.

[2] In the original model, the innovation process consists of four stages. Many subsequent papers point out that "whether to invest" and "how much to invest" are always decided simultaneously and could be combined.

[3] The average market share of the sampled manufacturing firms is quite small. It implies that firms do not have enough power to influence market price, so we assume a perfect competition.

production outputs and costs to enlarge the profit via the potential channel of innovation.

The profit maximization problem can be constructed as follows:

$$max \;\; \Pi = E[\pi]$$
$$s.t. \;\; E(\pi) = f\left(\widetilde{A}, I, X\right) - I \tag{3.1}$$

Firm's actual end-of-term profit π is unobserved at the time of making the R&D decision. Therefore, executives' goal is to maximize the anticipated profits $E[\pi]$. $f(\widetilde{A}, I, X)$ is the perceived profit that measures the predicted return. It counts all production costs other than R&D spending. I refers to the money amount planned to be invested in R&D activities, where $I \in (0, +\infty)$.

We further express the perceived profit as:

$$f(\widetilde{A}, I, X) = \widetilde{A}\, g(I, X, \widetilde{\varepsilon}) \tag{3.2}$$

$g(I, X, \widetilde{\varepsilon})$ is the actual return depending on firm's current conditions.[4] Without losing of generality, we assume $g(.)$ is a concave function with a diminishing return to the R&D input I, indicating that $g'(I) > 0$, $g''(I) < 0$ and $lim_{I \to 0} g'(I) = +\infty$. $g(.)$ also depends on a set of controls X, including the quantity and quality of factor inputs, internal and external conditions, etc. The unpredictable external shock $\widetilde{\varepsilon}$ also influences the actual profits with $E(\widetilde{\varepsilon}|X, I) = 0$.

Another component of the predicted return is a perceived parameter $\widetilde{A}$, which deviates predicted profit from its actual value. It captures leadership's perception of the profits gained from R&D, which is non-negative ($\widetilde{A} > 0$).[5] For the same level of R&D inputs I, a larger $\widetilde{A}$ means a higher perceived value evaluated by the leadership. Therefore, we further

[4] R&D improves production performance through both costs reducing (process innovation) and product creation (product innovation). These two channels cannot be distinguished in most cases. By viewing $g(.)$ as an aggregated effects of R&D on production, we do not take pains to identify the effect via each channel.

[5] We assume $\widetilde{A} > 0$ because the worst case scenario is to gain nothing. In this case, the firm attempts to avoid investing in R&D. The assumption $\widetilde{A} > 0$ rules out negative production expectation. We further assume $\widetilde{A} > 1$ means leadership overestimates the gain from innovation, while $0 < \widetilde{A} < 1$ means underestimation.

assume that the magnitude of $\widetilde{A}$ depends on leadership's "innovative human capital" H:

$$\widetilde{A} = \widetilde{A}(H) \tag{3.3}$$

To derive the optimal R&D investment level I^*, we take the first order condition with respect to the R&D investment I on the objective function:

$$\frac{\partial g(I^*, X, \widetilde{\varepsilon})}{\partial I} = \widetilde{A}^{-1} \tag{3.4}$$

On rearranging the above partial differential equation, we get the optimal level of R&D input as a function of managerial human capital H, firm controls X, and external shock $\widetilde{\varepsilon}$:

$$I^* = h\left(\widetilde{A}(H), X, \widetilde{\varepsilon}\right) \tag{3.5}$$

Based on the above analysis, leadership's managerial human capital influences a firm's R&D investment via perceived return. As we mentioned, a key problem is that managerial human capital H is unobserved. To measure the managerial human capital related to R&D propensity, we construct a similar framework from the last chapter. Borrow the same concept, an individual's human capital accumulated via inherent factors, formal education, and learning-by-doing over the lifetime. Among these channels, learning-by-doing is highly valued when leadership is appointed, and it also plays a crucial role in forming the vision of innovation. It is formed via different occupations, job tasks and some special experiences. Therefore, we express an individual's human capital as:[6]

$$hc_t = f(o_t, w_t, s_t, e_t, x_t) \tag{3.6}$$

As to whose human capital matters, we consider it from the angle of R&D decision-making process. The actual R&D investment is guided by R&D budget plan, which is

[6] The notations in the following expression is defined the same as in the last chapter.

usually proposed by CEO and approved by BOD at the end-of-year board meeting. Besides that, R&D adjustments in the implementation are also determined by CEO and BOD, such as follow-on or stop-loss strategy. Therefore, CEO and the collection of BOD's experiences help to widen a firm's managerial human capital spectrum, so it can be expressed as:

$$H = H(CEO, BOD) \tag{3.7}$$

$CEO = hc_t^{ceo}$ is CEO's personal human capital. $BOD = hc_t^{bod}$ is the aggregated human capital of BOD, which is a collection of each director's human capital.

To sum up, our hypothesis is that CEO and BOD's human capital, especially gained from the learning-by-doing, would influence firm's R&D decision with the potential channel of perceived profits towards the firm. These human capital factors can be reflected or measured by some special experiences. In the next section, we discuss which kinds of experiences of CEO and directors play important roles in R&D decision-making, as well as their influencing mechanism.

3.3 Data Resources and Variable Selection

We use the same database as in the last chapter, China Stock Market and Accounting Research Database (CSMAR). Our original samples are also the same as before, including all manufacturing firms listed on the Shanghai and Shenzhen Stock Exchanges in China, covering the period 2008 to 2016.

Due to the panel data structure in this specific case, we first drop the samples that only have one year of record in the database. They would be dropped automatically in estimation due to the missing values on lagged firm controls. We also drop the samples that only have two years of records because we use the second-lagged firm controls as the IV to address endogeneity. Finally, we drop the samples of the year 2008 because less than 25% of the firms (208 firms) report their R&D expenditure that year. After this process, we have an unbalanced panel with 11,257 firm-year observations for 1,593 firms.

Within this unbalanced panel, around 59% of the firms (941 firms) remained in the stock market for the entire sample period (Panel A, Appendix B.1). As for the yearly entry and delisting patterns, 741 firms entered the stock market during 2009-2014, while only 11 firms were delisted (Panel B, Appendix B.1). The year 2010-2011 has an "IPO peak" with more than 400 newly listed manufacturing firms. However, due to a new round of IPO regulation conducted by the China Securities Regulatory Commission, the number of newly-listed firms suddenly dropped after 2012.

This unbalanced panel structure may cause selectivity. The newly-listed and delisted firms may take different operational strategies during the first several years after entry or the last several years before delisting. The newly-listed firms are well-prepared to meet the IPO requirement before entry; here, we assume they take similar strategies and have comparable performance as other existing firms. Therefore, they are less likely to cause selectivity issues. In contrast, the delisted firms may cause selectivity due to poor performance and survival operations during the ST (special treatment) stage. However, due to the small number of delisted firms, the impact of selectivity should not be large.

3.3.1 Measures of CEO and BOD's Human Capital

As mentioned, CEO plays an important role in proposing R&D budget plan and implementing the actual investment, so CEO's human capital should be considered. The education level not only reflects one's knowledge reserve but also implies the inherent intelligence and learning ability (Hitt and Tyler, 1991; Wally and Baum, 1994). The well-educated CEO is more sensitive to new information, integrating it comprehensively and efficiently (Barker and Mueller, 2002) and reacting to it quickly and properly (Escriba-Esteve et al., 2009; Wincent et al., 2010), thus they are more capable of identifying market threats and opportunities. Finally, well-educated CEO has a better perspective and thus higher risk-tolerance towards high-risk high-return strategies. Therefore, they hold an optimistic and receptive attitude towards innovation activities (Kimberly and Evanisko, 1981).

With overseas experience, CEO gets more exposure to different modes of education, ways of social interaction, and patterns of corporate operation from abroad. Therefore, they have better learnability and flexibility to absorb and integrate the new information (Kedia and Mukherji, 1999). Moreover, the overseas CEO may have a deeper understanding of and better perspective toward new technology, thus valuing more highly the importance of innovation (Herrmann and Datta, 2002). Finally, getting access to foreign markets may also imply richer cognitive skills and external resources (Roth, 1995; Carpenter et al., 2001; Slater et al., 2009). However, overseas CEO prefers to promote technology in the cost-effective ways, such as utilizing innovation spillovers or purchasing existing techniques, rather than the risky R&D activities.

Existing papers provide empirical evidence that past career experiences in various functions have distinct impacts on R&D investment. Based on the upper echelon theory (Hambrick and Mason, 1984; Finkelstein and Hambrick, 1996), a CEO with the output experiences (marketing, innovation, etc.) aims at promoting corporate development through market expansion and new product discovery. Therefore, they view R&D as an irreplaceable approach to achieve sustainable growth. In this context, a CEO with innovation background is more sensitive to innovation activity. Innovative CEO also possesses sophisticated skills in R&D management and thus are more capable of and confident about selecting appropriate projects, and guiding R&D activities in practice.

In contrast, throughput experiences (finance, administration, production, law, etc.) emphasize the importance of operational efficiency in a firm's long-run growth. A CEO with the throughput experience views innovation as one among many methods to improve efficiency, and believe that it can be easily replaced by other cost-efficient and less risky strategies. In this context, a CEO with production experience may promote performance through process improvement, therefore tending to allocate more available resources on process adjustment. CEO's finance background may have dichotomous impacts on R&D

activities (Güner et al., 2008). Though a finance CEO may possess more financial resources, he/she may prefer to utilize them in financial strategies to gain acceptable profits rather than taking the high-risk R&D activities, because he/she has richer knowledge and stronger abilities in managing the firm's capital.

Many basic demographic characteristics also influence a CEO's expectation of R&D. An older CEO is more experienced to overcome the potential failure but becomes more risk-averse in general as age increases. A male CEO is more risk-tolerant in general when face uncertainty. However, these basic characteristics (age and gender) are highly collinear with the above-mentioned experience-based factors, so we drop them in the estimation.

Based on the descriptive statistics, around 83%-86% of the CEOs hold a bachelor's or higher degree with a gradually increasing trend during 2009-2016 (Table 3.1, Panel A). The proportion of overseas CEOs increases from 4.3% in 2009 to 8.9% in 2016. The proportion of CEOs with production experience increases steadily before 2014 and decreases after. In contrast, the proportion of CEOs with finance or innovation experiences increases drastically from 3.6% to 11.1%, and from 19.8% to 29.2% during the sample period, imply the growing attentions on CEO's industrial experiences in various functions.

As to BOD's experiences, we first consider the government background. It includes current position and previous experience. Public sector employees, especially the government employees, are generally more risk-averse due to the nature of job tasks (Buurman et al., 2012; Nicholson et al., 2019). Moreover, directors with government experience are assumed to be less creative with weaker industrial management skills due to a more bureaucratic career background (Lin et al., 2011). Further, current government employees potentially have broader political connections compared to ex-government employees. Therefore, they possibly have more external resources, including funding supports, innovation experts and legal insider information (Khwaja and Mian, 2005; Claessens et al., 2008). This resource advantage reduces the actual R&D risk, leading to an optimistic expectation towards the potential returns.

Table 3.1: Definition and Descriptive Statistics of CEO and BOD Factors

Variables	Definition	2009	2012	2016
A. CEO's Past Experiences				
Education_ceo ($c1$)	=1 if CEO holds a bachelor's or higher degree.	0.832 (0.374)	0.822 (0.383)	0.865 (0.342)
Overseas_ceo ($c2$)	=1 if CEO has either educational or industrial overseas experience.	0.044 (0.206)	0.061 (0.239)	0.089 (0.285)
Production_ceo ($c3$)	=1 if CEO has industrial production experience.	0.114 (0.318)	0.147 (0.355)	0.169 (0.374)
Finance_ceo ($c4$)	=1 if CEO has industrial finance experience.	0.036 (0.186)	0.068 (0.251)	0.111 (0.315)
Innovation_ceo ($c5$)	=1 if CEO has industrial innovation experience.	0.198 (0.399)	0.246 (0.431)	0.292 (0.455)
B. BOD's Past Experiences				
Education_bod ($b1$)	The proportion of board members with a bachelor's or higher degree.	0.821 (0.243)	0.839 (0.207)	0.876 (0.182)
Gov_pre_bod ($b2$)	The proportion of board members with a position in government previously.	0.151 (0.135)	0.146 (0.128)	0.085 (0.102)
Gov_cur_bod ($b3$)	The proportion of board members with a position in government currently.	0.089 (0.114)	0.089 (0.101)	0.066 (0.090)
Marketing_bod ($b4$)	The proportion of board members with marketing experience.	0.086 (0.105)	0.120 (0.122)	0.177 (0.138)

* Statistics in the first line for each variable is the mean, and in (.) is the standard deviation.

Directors with marketing background face various clients and a rapidly changing market. Therefore, they have better perspectives towards the products, market, and competitors, thus valuing the technology innovation in the market competition. Moreover, directors with marketing experience view innovation as one of the irreplaceable methods to discover new products and expand the market, supporting the firm's long-run growth. Finally, marketing directors potentially possess richer resources due to broader business cooperation and social network. These available resources (financial supports and human capital) raise directors' risk tolerance level towards R&D uncertainty.

Well-educated directors have similar influencing mechanisms as the highly educated CEO, including better perspectives and stronger sensitivity toward R&D. Following the same logic as for CEO's general characteristics, we drop other basic characteristics and general experiences, because they are potentially collinear with the experience-specific human capital factors mentioned above.

Unlike the CEO experience measures with dummy variables, we lack a direct measure of BOD factors, but have detailed information on each director. Therefore, we use the proportion of members with a certain experience to measure BOD background.[7] Based on the descriptive statistics (Table 3.1, Panel B), 82%-88% of directors hold a bachelor's or higher degree with a steadily increasing trend. The proportion of directors with marketing experience increases gradually from 8.6% at 2009 to 17.7% at 2016. The proportion of directors with a current government position remains stable before 2011 but drops from 9.7% to 6.6% since then. With the same pattern, the proportion of directors with previous government experience plunges from 14.9% to 8.5% after 2011. One possible reason is government regulation aimed at avoiding potential corruption and insider information leakage that limits the participation of government employees in the industry.

[7] According to the Company Law of P.R.C., each board member has equal voting power, and the proposals shall pass only when more than half of the members entitled to vote in favor (Article 48, Article 111). In this sense, "whether more than half of the board members possessing certain experience" seems to be a reasonable cutoff. However, even though the minority does not directly determine the final decision, they still have the influencing power through suggestion. Therefore, we adopt "the proportion of BOD with certain experience" to measure BOD's experiences.

3.3.2 R&D Intensity and Firm-level Controls

For the dependent variable of R&D input intensity, widely used indicators include the R&D expenditure to total asset ratio and the R&D expenditure to sales ratio. In general, the volume of total assets is more stable because it is less likely to be influenced by external shocks. Therefore, we adopt the R&D to total assets ratio as the measure to better reflect the internal R&D incentive (Hirshleifer et al., 2012; Sunder et al., 2017; Shaikh et al., 2018). Based on descriptive statistics (Table 3.2), the R&D to asset ratio is around 2.2% across years without a clear trend.

Table 3.2: Definition and Descriptive Statistics of R&D Ratio and Firm-level Controls

Variables	**Definition**	**2008 (2009)**	**2011 (2012)**	**2015 (2016)**
RD_ratio (%)	R&D to total asset ratio (percentage).	2.188 (1.718)	2.115 (1.558)	2.036 (1.544)
Num_employee ($fv1$)	Number of employees (logarithm).	4421 (7838)	4408 (9927)	5017 (11246
ROA ($fv2$)	Annual return to total asset ratio.	0.018 (0.243)	0.065 (0.596)	0.029 (0.077)
Liability_asset_ratio	Total liability to total asset ratio.	0.639 (3.345)	0.422 (0.503)	0.409 (0.215)
Market_share (%)	A firm's annual sales to the total sales of the "above designed sized firms" in the same sub-industry (in percentage).	0.213 (0.427)	0.161 (0.428)	0.159 (0.621)
State_owned ($fc1$)	=1 if a firm's actual controller is the central or local government.	0.513 (0.500)	0.325 (0.468)	0.290 (0.454)
Big_city ($fc2$)	=1 if a firm locates at big cities (Beijing, Shanghai, or Guangdong).	0.238 (0.426)	0.267 (0.442)	0.269 (0.444)

* The year in (.) is for the dependent variable R&D to asset ratio. Other controls have a one period lag.
* Statistics in the first line for each variable is the mean, and in (.) is the standard deviation.

To see the patterns of the sub-sample, state-owned firms have a 9.3% lower R&D intensity than the private firms. Tech-intensive firms, such as the high-tech, machinery, and transportation enterprises, have a larger R&D ratio compared to the traditional manufacturing firms (Appendix B.2). R&D ratio in both sub-sectors are relatively stable without clear time trend. Geographically, firms located in the eastern region of China have the highest R&D ratio of 2.2%-2.4%, followed by the firms in the central region with 2.0%-2.1%. The firms located in the northeastern and western regions has the lowest average R&D ratio below 1.8%.[8] More specifically, manufacturing firms located in developed region (Beijing, Shanghai, and Guangdong) have an average R&D ratio of around 2.3% to 2.6%, significantly higher than that of 1.9 to 2.1% in other developing provinces.

For firm-level controls, larger firms may have a higher risk capacity for R&D failure due to physical, financial, and human capital resource abundance (Fisher and Temin, 1973; Kamien and Schwartz, 1975). Large firms are also more productive in innovation due to the economies of scale, specialization, and lower entry barriers.[9] Firms with stronger market share have the advantages of gathering and integrating available resources, further supporting R&D activities.[10] However, firms with larger market share face fewer threats from the competitors, and thus focus more on smooth operation and efficiency improvements instead of radical changes (Hansen and Hill, 1991).

Firm's profitability and financial constraints measure the funding accessibility and financial liquidity. More profitable and less financially restricted firms possess sufficient financial supports to pursue R&D projects and face the potential failure risk, so they have higher incentives to pursue innovation (Long and Ravenscraft, 1993). However, poor profitability may motivate the firms to make radical changes to maintain long-run growth (Hitt et al., 1991). In this paper, we adopt the return to asset ratio (ROA) and the liabilities to asset ratio as the measures of profitability and financial constraints, keeping the consistent

[8] (1) Eastern: Shanghai, Beijing, Tianjin, Shandong, Guangdong, Jiangsu, Hebei, Zhejiang, Hainan and Fujian Province; (2) Central: Anhui, Shanxi, Jiangxi, Henan, Hubei and Hunan Province; (3) Northeastern: Jilin, Liaoning and Heilongjiang Province. All other provinces are defined as part of the western region.

[9] Sales and profits are directly influenced by outside market conditions, with quick reactions and drastic fluctuation. Therefore, they may lead to endogeneity sourced by the omitted external condition variables. Therefore, we adopt the number of employees as a stable measure of firm size.

[10] Since the direct measure for market share or the total market capacity is unavailable, we adopt the "above designed sized firms" as the proxy for total market sales. See Table 3.2 for details.

scaling method with the dependent variable.

For the ownership structure, state-owned enterprises (SOEs) have more financial and other supports from the government. SOEs also attract more resources due to their high reputation, such as skilled experts. However, SOEs have lower operation efficiency or flexibility due to hierarchical structure under government controls. Moreover, SOEs lack the incentives to make radical changes due to comparative advantages in market competition. For the geographical location, the industrial clusters in the big cities promote R&D activities due to the stronger scale effect, larger technology spillovers, lower transmission costs, and potential R&D cooperation. Moreover, the innovative environment and resource accessibility in big cities may also encourage innovation efforts.

Based on the descriptive statistics, firm size measured by the number of employees increased gradually during 2008-2015 (Table 3.2). ROA fluctuated between 1.8% and 6.5%, and the liabilities to assets ratio has a downward trend from 63.9% to 40.9%. The average market share is small in both magnitude and variation across firms. The proportion of SOEs decreases drastically from 51.3% to 29.0%, indicating that more private firms entered the A-share market in recent years due to market liberalization. Finally, the proportion of firms located in developed regions also increased slightly from 23.8% to 26.9%.

3.4 Baseline Specification

Based on the discussion in the theoretical framework, we construct the baseline model:

$$RD_{i,t} = \beta_1 CEO_{i,t} + \beta_2 BOD_{i,t} + \beta_3 fc_i + \beta_4 fv_{i,t-1} + DInd_i + DYear_t + c_i + \varepsilon_{i,t} \quad (3.8)$$

where $RD_{i,t}$ is the R&D to total asset ratio of firm i at year t. $CEO_{i,t}$ and $BOD_{i,t}$ are vectors of human capital factors for CEO and BOD at the current period. Firm-level controls are categorized into time-variant and time-invariant groups. The time-invariant controls fc_i include ownership status and geographic location. The time-variant firm controls $fv_{i,t-1}$

include firm size, profitability, financial constraints, and market share, with a one-period lag.[11] c_i is the firm's unobserved fixed effects, and $\varepsilon_{i,t}$ is the idiosyncratic error. We also control the year and sub-industry heterogeneity by adding two groups of dummies, $DYear_t$ and $DInd_i$.

We first adopt pooled OLS estimation because it only requires the weakest contemporaneous exogeneity assumption. Based on the results, CEO with a bachelor's or higher degree raises R&D inputs, while this positive association becomes insignificant after controlling BOD's experiences (Table 3.3, Column 1 and 2). The collinearity between CEO education and BOD factors might be the explanation. An overseas CEO leads to a lower R&D ratio, but it is both statistically and economically insignificant regardless of controlling for BOD factors or not. CEO's production and finance experience hinder R&D percentage ratio significantly by 0.22 and 0.27 respectively, while the innovation background increases R&D ratio in percentage by 0.24. These impacts are still significant after controlling for BOD factors, only with marginal magnitude changes.

For BOD's experiences, a highly-educated BOD promotes R&D inputs significantly. A 10% increase in directors with a bachelor's or higher degree increases R&D ratio by 0.11, equivalent to 5.8% of its average level. BOD's marketing experience also has a significant positive impact that every 10% more members with the marketing experience lead to a 0.04 higher R&D ratio in percentage. The proportion of directors with previous government background has a significant negative impact on R&D incentives, whereas the impact of current government position is insignificant.

As to firm controls, the results are consistent with those in the previous literature. Firm size and profitability are positively associated with R&D inputs. Every 1% expansion of firm size leads to a 0.2 larger R&D percent ratio. Firms with larger market power or financial restriction have a significantly lower R&D intensity compared to others. SOEs

[11] Reasons to take a one-period lag: (1) Primary reason: doing so helps to avoid the potential endogeneity caused by simultaneous or reverse causality; (2) also, when making R&D decision, CEO/BOD refer to firm's conditions at the end of previous year rather than the unobservable one at the end of current period.

Table 3.3: Pooled OLS and Random Effect

	Pooled OLS		Random Effect	
	CEO	CEO+BOD	CEO	CEO+BOD
A. Managerial Human capital				
$Education\_ceo_{it}$	0.2492***	-0.0117	0.1665***	0.1164**
	(0.0423)	(0.0491)	(0.0540)	(0.0567)
$Overseas\_ceo_{it}$	-0.0867	-0.0928	0.0362	0.0242
	(0.0662)	(0.0653)	(0.0708)	(0.0707)
$Production\_ceo_{it}$	-0.2185***	-0.2072***	-0.0500	-0.0551
	(0.0466)	(0.0468)	(0.0529)	(0.0529)
$Finance\_ceo_{it}$	-0.2713***	-0.2582***	-0.1105	-0.1204*
	(0.0574)	(0.0573)	(0.0673)	(0.0673)
$Innovation\_ceo_{it}$	0.2421***	0.2327***	0.0831*	0.0874**
	(0.0461)	(0.0463)	(0.0440)	(0.0440)
$Education\_bod_{it}$		1.1422***		0.3899***
		(0.1200)		(0.1415)
$Gov\_pre\_bod_{it}$		-0.6183***		-0.1948
		(0.1492)		(0.1346)
$Gov\_cur\_\_bod_{it}$		-0.0663		0.2832*
		(0.1935)		(0.1629)
$Marketing\_bod_{it}$		0.3681**		0.3757**
		(0.1560)		(0.1511)
B.Firm-level Controls				
$\ln(num\_employee)_{i,t-1}$	0.2200***	0.2134***	0.1392***	0.1373***
	(0.0250)	(0.0248)	(0.0267)	(0.0266)
$ROA_{i,t-1}$	2.0355***	2.0096***	0.5447***	0.5473***
	(0.5895)	(0.5810)	(0.1801)	(0.1802)
$Liability\_asset\_ratio_{i,t-1}$	-0.7130***	-0.6867***	-0.2001*	-0.1842
	(0.1327)	(0.1329)	(0.1121)	(0.1122)
$Market\_share_{i,t-1}$	-0.2855***	-0.2697***	-0.1153**	-0.1131*
	(0.0670)	(0.0635)	(0.0585)	(0.0585)
$State\_owned_i$	-0.2047***	-0.2687***	-0.2666***	-0.2840***
	(0.0481)	(0.0504)	(0.0861)	(0.0861)
Big_city_i	0.4172***	0.3461***	0.4143***	0.3790***
	(0.0492)	(0.0478)	(0.0831)	(0.0830)
Constant	-0.4542**	-1.0479***	0	-0.4720*
	(0.2208)	(0.2327)	(.)	(0.2671)
Observation	5775	5770	5775	5770
Adjusted R-square	0.1831	0.1966		
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

* The significance level: ***0.01, **0.05, *0.1

have a 0.27 lower R&D percent ratio compared to private firms. Finally, firms located in the developed regions tend to invest more in R&D compared to those located in the developing cities or towns.

Taking advantage of the panel data structure, we further adopt the random effect (RE) to improve the efficiency. Based on the results (Table 3.3, Column 3 and 4), a highly-educated CEO leads to a significantly higher R&D ratio whether control for BOD experiences or not. CEO's throughput functional experiences are still negatively related to R&D investment, but the impact of production experience becomes insignificant. An innovative CEO still raises the R&D investments. Directors' formal education and marketing experiences spur the R&D ratio by 1.8% and 1.7% respectively for every 10% more members with these corresponding experiences. Directors' previous government experience hinders R&D incentives, though it is insignificant, while directors' current government position has a positive impact.

The potential explanation for the differences between pooled OLS and RE estimation is that pooled OLS ignores the variance-covariance structure of the composited error term. RE method improves the efficiency at the cost of a stronger strict exogeneity assumption, which is less likely the case. Therefore, by using pooled OLS and RE as the complement for each other, we can see a relatively consistent story and broad picture of the influencing direction and significance of the managerial human capital factors.

3.5 Endogenous Process of CEO Appointment

Above baseline estimation has shown the strong impact of human capital characteristics of corporate leadership on R&D investment. In this section, we further investigate and address the potential endogeneity issue of some human capital features. It is likely that CEO's appointment and renewal process might depend on a firm's goals and plans, including the innovation. We assume that CEO's experiences are associated with the unobservable heterogeneity c_i in equation (3.8).

For publicly listed firms, BOD is usually composed of the largest shareholders, shareholders' representatives and selected agents. Most directors may have close social relationship with the shareholders due to the subjective and exclusive nature of BOD appointment (Fama and Jensen, 1983). Therefore, BOD experiences may be closely related to shareholders' control power and preference, while weakly related to firm-specific determinants (Li, 1994; Denis, 1999). Existing literature also supports this weak relationship by providing test-based evidences, so we assume BOD factors are exogeneous (Kor, 2006; Bravo and Alvarado, 2017).

The actual amount of R&D investment is usually proposed by CEO and approved by BOD at the end-of-year board meeting, largely depending on firm's condition at that time point. Therefore, one-period lagged firm controls have strong deterministic power on R&D decision. As mentioned, adopting lagged controls avoids potential endogeneity issue in large extent. Random shocks in the current or future periods will not influence firm's financial condition or other traits in the previous period, so $E(fv'_{i,t-1}\varepsilon_{i,t}) = 0$, largely reducing omitted variable bias. Moreover, lagged controls also help to avoid reverse or simultaneous causality, since firm's conditions in the previous year will influence the decision on current R&D inputs, but not the other way around.[12] In this case, we assume both BOD factors and lagged controls are independent from the external shock $\varepsilon_{i,t}$, and remotely related to firm's fixed heterogeneity.[13]

The widely used way to address the endogeneity with panel structure is the Fixed Effect (FE). However, endogenous CEO factors change rarely over time due to the nature of dummy variables. The descriptive statistics also provide evidence in support of the almost-invariant assumption on CEO factors, that the within-variation of each CEO factor is only around 10%-20% during 2009-2016, even though CEO turnover rate is high (Appendix B.3).[14] Therefore, CEO variables may lose within-variation after doing time-demean or

[12] Financial status in current year maybe influenced by R&D investment in the same period.

[13] The potential endogeneity of firm controls and BOD factors are much weaker compared to that of CEO factors. Therefore, if any, we simply ignore it.

[14] CEO's factors change only when CEO turnover occurs, or a small number of CEOs gain new experi-

first-difference, so FE and FD methods are not applicable in our specific case.

Random Effect - Instrument Variable approach (RE-IV) is therefore adopted. Instead of seeking external instruments, we select IV candidates from within the panel system based on the Hausman-Taylor method (HT). HT provides two groups of internal IV candidates: (a) the time-demeaned time-variant variables, no matter endogenous or exogeneous, $z_1 = [\ddot{BOD}_{i,t}, \ddot{fv}_{i,t-1}]$;[15] (b) time-variant exogenous variables in all periods that are not redundant, $z_2 = [BOD^0_{i,s}, fv^0_{i,s-1}](s = 1, \ldots, T \text{ and } s \neq t)$.[16] Besides satisfying the IV assumptions, these two sets of internal IV also make sense in terms of mechanism, because CEO selection is decided by BOD or owners based on their concerns on whether candidates fit the objective condition. Moreover, BOD appointment may also be influenced by the CEO factors due to a bargaining process (Hermalin and Weisbach, 1988). Thus, instruments that related to firm characteristics and BOD experiences should be correlated with the endogenous CEO variables.

However, the large number of potential IV candidates may lead to substantial finite sample bias due to overidentification, so we only choose a subset of candidates which are most relevant to CEO appointment.[17] CEO's assignment decision is closely related to firm's condition and BOD factors at the most recent, while these factors at other periods have the relatively remoter impacts. First, CEO appointment or turnover decision is usually made by BOD at last year due to bargaining process, so current CEO factors should be highly-related to BOD factors in last period (Tian et al., 2011). Moreover, whether a CEO candidate fits firm's objective conditions at the time of making the turnover or appointment decision is the most important concern, so the latest firm conditions are also the convincing IV. In this case, we only keep the first-lagged BOD factors and the second-lagged firm controls in z_2.

ences. Even if CEO turnover occurs, the experiences may not change between the predecessor and successor.

[15] Any director change may lead to the change of each BOD factor. Moreover, outside directors are likely to gain new experiences. Therefore, we assume BOD factors are time-variant. The statistics also support that around 80-90% of the firms have a change of each BOD factor during 2009-2016.

[16] The superscript "0" in $BOD^0_{i,s}$ and $fv^0_{i,s-1}$ means the non-redundant variables at period s and $s-1$.

[17] Assuming the number of variables in CEO, BOD, fc and fv are N_1, N_2, N_3 and N_4 respectively, and the number of time periods is T. We have $(N_2 + N_4)$ internal IV candidates in the first group and $(T-1) \times (N_2 + N_4)$ in the second, thus totally have $T \times (N_2 + N_4) = 64$ from within the panel system.

In z_1, we keep most of $\ddot{BOD}_{i,t}$ due to BOD's duty in CEO appointment. $\ddot{BOD}_{i,t}$ indicates the potential personnel change on BOD, leading to a preference change on CEO turnover, so it may be associated with CEO factors.[18] However, the short-run turbulent factors at firm-level (profitability, financial and market condition) might not lead to the immediate actions on CEO turnover due to high costs, though they may have the long-run effect.[19] In contrast, the structural conditions, such as firm size, are the main concerns when BOD assigns or change the CEO. Therefore, we only keep the time-demeaned firm size as the instruments. Finally, we have a comparable number of IV:[20]

$$IV = \left[fv1_{i,t-2},\ \ddot{fv1}_{i,t-1}, b1_{i,t-1},\ b2_{i,t-1}, b3_{i,t-1},\ b4_{i,t-1},\ \ddot{b1}_{i,t}, \ddot{b3}_{i,t},\ \ddot{b4}_{i,t}\right]$$

These IV candidates are assumed to follow the exclusion restriction assumption. They do not have the direct impacts on R&D investment, because the impacts of BOD and firm controls at previous periods on current R&D expense are relatively remote. However, they still influence R&D inputs indirectly through the potential channel of CEO appointment.

Based on the results (Table 3.4), after addressing the endogeneity, highly educated CEO has an insignificant impact on R&D strategy regardless of controlling BOD factors or not. One potential reason is that the theoretical knowledge acquired from education is less important than the practical skills gained via learning-by-doing. Moreover, CEO education is potentially correlated to other factors controlled in the model, so its impact is partially absorbed and thus becomes insignificant.[21]

CEO's overseas experience also has an insignificant impact on the R&D investment. First, the net effect of both the positive and negative impacts might be the reason. The better perspectives towards innovation, higher risk-tolerance and richer resources all contribute to the positive impact, while the negative impact may come from the market adaptability. Sec-

[18] We ignore the time-demeaned BOD previous government experience, because it has small within-variation and is remotely related to CEO appointment.

[19] Some evidences are found in corporate case studies and interview reports in China.

[20] The notation of each variable is given in Table 3.1 and Table 3.2. Detailed explanation of RE-IV methods, including instrument selection and assumptions are in Appendix B.4.

[21] When we regress CEO education dummies on all other variables, the R^2 gives a 0.3 value.

Table 3.4: Pooled 2SLS and RE-IV (Hausman-Taylor)

	Pooled 2SLS		RE-IV	
	CEO	CEO+BOD	CEO	CEO+BOD
A. Managerial Human capital				
$Education\_ceo_{it}$	1.1435***	-0.4051	0.3822	-1.0400
	(0.3017)	(1.1996)	(0.2902)	(0.7004)
$Overseas\_ceo_{it}$	-0.0168	-1.8700	2.4095*	1.2339
	(1.4735)	(2.1111)	(1.3074)	(1.1815)
$Production\_ceo_{it}$	-0.4827	-0.8374	-1.7456**	-2.5686***
	(0.9155)	(1.1126)	(0.7061)	(0.7334)
$Finance\_ceo_{it}$	-3.4351**	-2.8711	-1.6472*	-2.6301**
	(1.4338)	(2.0910)	(0.9796)	(1.1143)
$Innovation\_ceo_{it}$	-0.3046	1.8741**	1.2790**	1.7918***
	(0.7137)	(0.8905)	(0.5823)	(0.5609)
$Education\_bod_{it}$		1.139		1.3409**
		(1.1693)		(0.6410)
$Gov\_pre\_bod_{it}$		-0.6070**		-0.2138
		(0.2996)		(0.2142)
$Gov\_cur\_\_bod_{it}$		0.0084		0.0521
		(0.3807)		(0.2678)
$Marketing\_bod_{it}$		0.7219***		0.6348**
		(0.2729)		(0.2521)
B. Firm-level Controls				
$\ln(num\_employee)_{i,t-1}$	0.1895***	0.2750***	0.1304***	0.2126***
	(0.0481)	(0.0547)	(0.0391)	(0.0427)
$ROA_{i,t-1}$	1.8652***	1.5340**	0.4492*	0.2306
	(0.6851)	(0.6282)	(0.2514)	(0.3014)
$Liability\_asset\_ratio_{i,t-1}$	-1.0458***	-0.6718***	-0.1438	-0.4328**
	(0.2141)	(0.2428)	(0.1879)	(0.2053)
$Market\_share_{i,t-1}$	-0.2659**	-0.5222***	-0.1870**	-0.2766***
	(0.1115)	(0.1440)	(0.0882)	(0.0960)
$State\_owned_{i}$	-0.2711***	-0.3753***	-0.1313	-0.155
	(0.0971)	(0.1206)	(0.1478)	(0.1236)
Big_city_{i}	0.3975***	0.4255***	0.2009	0.2021*
	(0.1136)	(0.1366)	(0.1409)	(0.1209)
Constant	-0.6184	-1.2650***	-0.4643	-0.7841**
	(0.3799)	(0.4490)	(0.3915)	(0.3748)
Observation	5103	5103	5103	5103
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

* The significance level: ***0.01, **0.05, *0.1

ond, some CEOs only take overseas positions nominally without substantive work, so they are hard to be distinguished from those without overseas experience. Finally, the "learning adjustment" may affect the effectiveness of overseas experiences. Short-term overseas education or employment may have marginal impacts on human capital accumulation due to the time-consuming nature of adjusting to new environment.

Among CEO's industrial experiences, two throughput backgrounds (finance and production) still have negative and significant impacts on R&D inputs. They reduce the R&D ratio in percent by 2.6, equivalent to 36.4% of its average level. Innovative CEO significantly raises R&D ratio in percent by 1.8, equivalent to 81.8% of the average ratio. The above empirical results support the upper echelon theory that CEOs with throughput functional experiences view R&D activities as one of many alternative methods to improve efficiency. In contrast, CEOs with output experiences value the importance of R&D in long-run development. The results also point out that the practical experiences gained from "learning-by-doing" have more practical value in devising R&D strategy.

For BOD's factors, every 10% more highly-educated directors lead to 0.13 higher R&D ratio, equivalent to 5.9% of its average level. The possible explanations are similar to those of the well-educated CEO, including broader horizon on innovation and stronger managerial skills. Marketing experience promotes R&D inputs via the potential channels of better perspectives and sensitivity to the market, products, and firm operations. It is supported by the evidence that every 10% more members with marketing experience significantly raise R&D ratio by 0.07, equivalent to around 3% of its average level.

Previous government experience is negatively correlated with R&D incentives due to the risk averse attitude. With 10% more directors who previously worked in government sector, R&D ratio significantly drops 0.02 to 0.06, equivalent to 1%-2.7% of its average level. In contrast, directors' current government positions have an insignificant impact with the potential explanation of the net effect. Richer human capital resources, stronger financial supports, and legal insider information may incentivize a firm to pursue R&D

activities, which potentially offset the negative impact caused by the risk aversion attitude of government employees.

Comparing the results of the baseline model and endogeneity-adjusted estimation, the latter have larger magnitudes in general, especially the CEO's factors. These results support our hypothesis that the CEO's experiences are endogenous. In the baseline estimation, the impacts of CEO's experiences may be partially absorbed by the unobserved heterogeneity. This difference in the results is particularly evident in the CEO's functional experience, which further emphasizes the importance of industrial experiences on a firm's strategical decision-making.

3.6 The Long-run Impact of Managerial Human Capital

R&D investment may be affected by its past values (Zona, 2016; Shaikh et al., 2018). For example, a large investment in previous year may cause more follow-on investments or less spending in current year depending on the nature and progress of these projects. Moreover, the human capital variables and firm controls may have lasting impact on R&D. For instance, the profitability in the last several years may all contribute to the current R&D inputs. Therefore, inclusion of lagged R&D can capture these effects and mitigate the potential omitted variable bias.

We adopt AR(1)-type of specification to capture the dynamics of R&D investment:[22]

$$RD_{i,t} = \gamma \cdot RD_{i,t-1} + \beta_1 CEO_{i,t} + \beta_2 BOD_{i,t} + \beta_3 fc_i + \beta_4 fv_{i,t-1} + DInd_i + DYear_t + c_i + \varepsilon_{i,t} \quad (3.9)$$

In general, it is common to adopt IV or GMM methods, such as the Arellano-Bond approach, to estimate a dynamic panel model, addressing endogeneity caused by the correlation between c_i and $RD_{i,t-1}$ (and also $CEO_{i,t}$).[23] These approaches build upon the first

[22] Based on the empirical evidence from the previous literature, we assume the autocorrelation dies out quickly and that AR(1) is enough to capture the past R&D investment information.

[23] These methods include but are not limited to Anderson-Hsiao, Arellano-Bond, Arellano-Bover and Blundell-Bond. Current R&D input is irrelevant to the future shocks, so $E(RD'_{i,t-1}\varepsilon_{i,t}) = 0$, though it might be related to current or previous shocks. Furthermore, it should be associated with the unobservable

differencing of equation (3.9), which aim to remove c_i and then find appropriate IV for $\Delta RD_{i,t-1}$. However, due to the rarely-changing nature of CEO's experiences, taking FD may significantly reduce the within-variation and therefore lead to inconsistent estimates.[24]

To address this issue, we take a similar strategy used in the last chapter. We expand the HT-type of RE-IV in the static model, applying it on level-equation (3.9) instead of taking first-difference on it. The only difference between the dynamic and static model is the endogenous term $RD_{i,t-1}$. Therefore, in the implementation, we only add one more IV for $RD_{i,t-1}$, which is $\Delta RD_{i,t-1}$, and keep all existing IV from the static model.[25] The advantages include: (a) it provides consistent estimates under rarely-changing assumption for the independent variables; (b) the interpretations are comparable to those in the static models due to a consistent estimation strategy.

Based on the results (Table 3.5), lagged R&D investment has a significantly positive impact on current R&D inputs with an estimate of 0.4-0.5. This relationship supports our above-mentioned hypothesis that a firm makes its current R&D investment decision by referring to its past value, and a consistent R&D strategy is preferred. The estimated coefficient for lagged R&D ratio is less than one, implying a stationary process that the impact of past R&D investment converges to zero in the far future. From a dynamic perspective, CEO and BOD's human capital also has an accumulated lasting impact on R&D strategy through the lagged R&D in the long-run.

CEO with a bachelor's or higher degree has an insignificant impact on R&D investment regardless of controlling for BOD's factors or not. Overseas CEO leads to a 1.4 higher R&D ratio, equivalent to 64% of its average level. Overseas CEO may have stronger cognitive skills, better perspectives, and broader horizons, so he/she is more sensitive to a firm's current condition and actively adjust R&D strategies accordingly. In the long-run, a

FE due to inclusion, and therefore $E(RD'_{i,t-1}c_i) \neq 0$.

[24] We check the change rate of CEO variables, most of them are under 10%, so within-variation is low.

[25] Arellano-Bover and Blundell-Bond proved that all $\Delta RD_{i,s-1}(s = 2, \ldots t)$ could be IV candidates for $RD_{i,t-1}$. To avoid overidentification, I only adopt $RD_{i,t-1}$. The reasons are (a) it is more closely related to $RD_{i,t-1}$; (b) it can be expressed as the FD of all lagged FD of the dependent variable, time-variant independent variables, and idiosyncratic error, so containing all information of all other IV candidates.

Table 3.5: Dynamic model with RE-IV (Hausman-Taylor)

	CEO	CEO+BOD
A. Managerial Human capital		
Education_ceo $_{it}$	0.0105	-0.9257
	(0.1529)	(0.5858)
Overseas_ceo $_{it}$	1.4072**	2.3329***
	(0.5841)	(0.7751)
Production_ceo $_{it}$	-1.9604***	-1.5452***
	(0.4413)	(0.4898)
Finance_ceo $_{it}$	-0.2055	-0.5284
	(0.6094)	(0.8360)
Innovation_ceo $_{it}$	0.9685***	1.4275***
	(0.3264)	(0.4223)
Education_bod $_{it}$		1.0330
		(0.6340)
Gov_pre_bod $_{it}$		-0.3769*
		(0.1952)
Gov_cur__bod $_{it}$		-0.2985
		(0.2376)
Marketing_bod $_{it}$		0.3331
		(0.2048)
B. Firm-level Controls		
RD_ratio $_{i,t-1}$	0.5157***	0.3998***
	(0.0121)	(0.0395)
ln(num_employee) $_{i,t-1}$	0.2100***	0.2221***
	(0.0334)	(0.0386)
ROA $_{i,t-1}$	0.2047	0.156
	(0.3104)	(0.3159)
Liability_asset_ratio $_{i,t-1}$	-0.5362***	-0.5179***
	(0.1534)	(0.1803)
Market_share $_{i,t-1}$	-0.2006***	-0.2191**
	(0.0706)	(0.0858)
State_owned $_{i}$	-0.0069	-0.0575
	(0.0631)	(0.0825)
Big_city $_{i}$	0.0143	0.0425
	(0.0581)	(0.0759)
Constant	-0.8276***	-1.0377***
	(0.2636)	(0.3145)
Observation	4190	4190
Industry FE	Y	Y
Year FE	Y	Y

* The significance level: ***0.01, **0.05, *0.1.

firm with overseas CEO has an accumulative 2.76 higher R&D ratios in a long-run frame compared to those firms without overseas CEOs.

For the career experiences in various functions, production experience significantly reduces R&D ratio by 1.5-1.9, equivalent to 72.7%-89% of its average level. Innovative CEO spurs R&D ratio by 0.97-1.43, equivalent to 45.5%-65% of the average level. In contrast, finance experience has a negative but insignificant impact. Based on the results, innovative CEO is more sensitive to the opportunities and threats in pursuing R&D activities, so he/she has higher incentives to invest more in R&D activities. These results are broadly consistent with those literature explaining the result with Upper Echelon theory. To see the long-run effects, the accumulative impacts of production or innovation experiences are around -3.9 and 1.9, respectively.

For BOD's experiences, every 10% more directors with a bachelor's or higher degree leads to 0.1 higher R&D ratio in percent, equivalent to around 4.7% of its average level. For some special experiences, every 10% more members with the previous government experience impede the R&D ratio significantly by 0.04 as a result of risk aversion, comparable to 1.7% of its average level. In terms of long-run impact, every 10% more directors with previous government background would lead to an accumulative 0.08 lower R&D ratio in the future. In comparison, the impact of BOD's current government position is insignificant due to the potential net effect of risk aversion and resource abundance. For industrial experiences, 10% more members with marketing experience raise the R&D ratio in percent by 0.03, equivalent to around 1.5% of its average level. Though the impacts of marketing experience and formal education are insignificant at 10% level in dynamic perspective, the direction tells a consistent story with static view.

Based on above results, after controlling for lagged R&D strategy, most of human capital factors still show significant impacts on R&D expenditures. These results imply that CEO and BOD play important roles in R&D decision-making due to their active participation in daily operation and their decision-making power. However, some human capital factors, such as CEO's finance background and BOD's marketing experience, become insignificant after controlling the time-trend of R&D inputs. One possible explanation is that lagged R&D inputs contain lagged human capital factors, so they have multicollinearity issue with human capital factors at current period, leading to the insignificant impacts.[26]

3.7 Conclusion

In this chapter, we investigate the relationship between managerial human capital and corporate R&D incentives. We use various specific experiences of both CEO and BOD as novel measures of human capital characteristics, potentially reflecting their unobserved managerial skills, perspectives, and risk attitudes.

We find that the CEO and directors' career experiences in various functions have significant impacts on R&D investment. In particular, innovation experiences in (R&D or design) and marketing are positively associated with R&D investment, while previous experiences in production and finance have negative impacts. Production and finance backgrounds reduce the R&D percentage ratio by 1.6 and 1.7 respectively, equivalent to 72.7% of its average level; in contrast, past experience with innovation-related work leads to a 1.3 percent points increase in R&D input ratio. Moreover, 10% increase in BOD members with marketing experience can raise the average R&D investment level by around 0.03 percent point%. 10% more directors with previous government backgrounds significantly reduces R&D ratio by 0.05 percent point.

For other human capital factors, the high-educated board leads to a larger amount of R&D investment. Directors' past government experience reduces R&D spending significantly while current government positions have a statistically insignificant impact. The impact of the CEO's overseas experience is ambiguous and sensitive to different model setups. It has a significantly positive impact on R&D investment in a dynamic frame.

[26] We regress lagged R&D on all other variables, getting an 0.17 R^2 with p-value for F-test of 0, so the multicollinearity may exist.

CHAPTER 4
RISK ATTITUDE, DEBT TOLERANCE AND HOUSEHOLD INVESTMENT BEHAVIOR

4.1 Introduction

To have a broad picture of how human capital influences different levels of national economy, we then expand our research to household-level. In recent years, the vital financial market in China provides investors with wide variety of financial products to allocate assets, smooth intertemporal consumption and accumulate wealth. Household's financial participation, in turn, raises enterprise's capital, and promote persistent economy growth. [1] However, the financial participation rate in China does not reach anticipated level. Based on the statistics, "insufficient financial knowledge" and "limited household wealth" are two major reasons, accounting for 52.51% and 50.72%. "The risk is too high" accounts for 18.65% and "never heard about certain financial instruments" accounts for 10%. The portfolio composition and trading behaviors also corroborate above concerns. Large majority of investors prefer a smoother long-term or mid-run investment strategy rather than a short-term or high-frequency trading.[2] For portfolio composition, top three methods to allocate wealth are stock purchase, bank financing and bank deposits. Among all stock investors, 48.8% mainly invested in main board or SME board, 10.8% in GEM, while only 4.4% preferred STAR (Sci-Tech).

Many researchers are thus interested in identifying the influencing factors of investment decision. The objective conditions set financial constraints for investors, such as wealth, income and family features (Agnew et al., 2003; Rosen and Wu, 2004; Campbell,

[1] The individual investors in China only have a 11.45% stock participation rate (160 million). These and all following statistics come from *the report of investors in the national stock market survey (2019).*

[2] 38.1% prefer the "band operation in middle-term", 35.2% prefer the "value investing in long-term", and only 17.9% prefer the "fast-in fast-out in short-term".

2006). Existing papers also discussed how one's interaction with external environment influence investment behavior, such as social interaction and peer effects (Hong et al., 2004; Kaustia and Knüpfer, 2012; Li, 2014; Liang and Guo, 2015). However, these factors only partially or indirectly explain one's motivation on financial behavior, but the importance of human capital is always neglected or seldom discussed (Feng and Seasholes, 2005).

A line of papers explored how household head's human capital influences financial decision and performance. Demographic characteristics and general experiences, including gender, age, education, etc., reflect unobserved cognitive ability and personality, so acting as the measures for individual's human capital to some extent (Barber and Odean, 2001; Almenberg and Breber, 2015; Gomes and Michaelides, 2005; Christiansen et al., 2008).

Besides these indirect and composited measures, many papers also discussed some specific human capital factors. For instance, the cognitive skills, measured by test-scores, are found to have significant impact on financial behavior (Guiso and Jappelli, 2005; Christelis et al., 2010; Grinblatt et al., 2011). The influencing channels include financial awareness, information constraints, etc.. For the relevant concepts related to cognitive ability, financial knowledge, literacy and efficacy are widely discussed (Rooij et al., 2011; Abreu and Mendes, 2010; Fernandes et al., 2014; Hsiao and Tsai, 2018). They are found not only to encourage households' investment in risky assets, such as stocks and other derivatives, but also to motivate the portfolio diversification.

As to personality traits, risk aversion in different domains potentially indicates household's risky investment propensity, but also implies the fraction of risky assets in households' asset portfolio (Cohn et al., 1975; Keller and Siegrist, 2006). Another relevant concept, ambiguity aversion, is also examined to be negatively related to the participation propensity and depth, while lead to higher portfolio diversification (Dimmock et al., 2016). Various types of personality traits also jointly influence households' financial decision. Risk tolerance interacts with the trust attitude to affect the risky investment decision, and they further lubricate the financial system and contribute to financial market development

(Bucciol et al., 2019). Household consumption decision and investment performance are influenced by financial literacy and risk attitudes jointly (Zhang et al., 2021). Exploring this topic in-depth is also of great value in Chinese cases, due to the current condition of immature market, asymmetric information and unskilled investors. Therefore, we further investigate how the participation decision, and its depth are influenced by specific human capital factors.

4.2 Theoretical framework

4.2.1 Model Setup

We first assume that each household has a following utility function $U(.)$ over its terminal wealth W based on constant-relative-risk-aversion (CRRA) preference assumption:

$$U(W) = \frac{W^{1-\gamma}}{1-\gamma} \tag{4.1}$$

$\gamma \in (-\infty, \infty)$ is a preference parameter, depreciating one's utility on the actual wealth level.[3] Larger γ means lower utility with the same wealth, implying more risk averse.

In a single-period model, an investor holds two types of assets, risk-free assets (treasury bond, deposits, etc.) with a risk-free interest rate $r_f = 0$, and a risky portfolio (stock, fund, etc.). The value change on risky portfolio during this period has a binary distribution, either going up by r_u with probability π, or dropping by r_d with probability $(1-\pi)$:

$$P(r = r_i) = \begin{cases} \pi, & i = u \\ 1-\pi, & i = d \end{cases} \tag{4.2}$$

Investor aims at maximizing expected utility by investing a fraction h of the initial wealth

[3] In our empirical work, we define a group of risk-loving person, so we allow γ to be smaller than 0.

w in risky portfolio, so we have:

$$max \quad \frac{\pi \left[w\left(1+hr_u\right)\right]^{1-\gamma}+(1-\pi)\left[w\left(1+hr_d\right)\right]^{1-\gamma}}{1-\gamma} \tag{4.3}$$

$$s.t. \quad 0 \le \pi \le 1, \quad 0 \le h \le 1$$

Therefore, the optimal proportion of wealth invested in the risky portfolio is given as:

$$h^* = \frac{1-m}{mr_u - r_d} \tag{4.4}$$

where $m = [-\frac{\pi r_u}{(1-\pi)r_d}]^{-\frac{1}{\gamma}} < 1.$

By plugging h^* back into the objective function, with the optimal terminal wealth w_p conditional on investing in risky portfolio, the terminal utility is:

$$U\left(w_p\right) = A\frac{w^{1-\gamma}}{1-\gamma} = U\left(aw\right) \tag{4.5}$$

where $A = (\frac{r_u - r_d}{mr_u - r_d})^{1-\gamma}[(1-\pi)m^{1-\gamma}+\pi] > 0$ and $a = A^{\frac{1}{1-\gamma}}$.

Only when the optimal excess return of risky investment surpasses its fixed costs c, investor would prefer risky investment:

$$w_p - w = \left(\alpha - 1\right) w > c \tag{4.6}$$

$G(c)$ is the cumulative distribution function of c, so the risk investment probability P is:

$$P = G\left[\left(\alpha - 1\right) w\right] \tag{4.7}$$

We take the F.O.C. on equation (4.4) and (4.7) with respect to the risk preference parameter γ and risk perception π, finding that:

$$\begin{cases} \dfrac{\partial h^*}{\partial \gamma} < 0 \, and \, \dfrac{\partial h^*}{\partial \pi} > 0 \\ \dfrac{\partial P}{\partial \gamma} < 0 \;\; and \;\; \dfrac{\partial P}{\partial \pi} > 0 \end{cases} \tag{4.8}$$

Results above indicate that risk averse persons are more reluctant to engage in risky portfolio and also invest less to it. Those who have better perspectives towards market and self-efficacy are more willing to participate in risky investment and invest more. Therefore, investment probability and depth are both decreasing functions of risk averse and increasing with market perception, as well as two sets of household factors, X_1 and X_2:

$$h^* = h(\pi,\ \gamma,\ X_1) \;\; and \;\; P = p(\pi,\ \gamma,\ X_2) \tag{4.9}$$

Detailed explanation and derivation of this subsection are in Appendix C.1.

4.2.2 The Nature of Risk Attitude and Perception

γ is risk attitude, which is a preference parameter. Based on the existing papers, preference is the natural counterpart of human capital, especially one's personality traits. Though the causal relationship between risk attitude and human capital factors remains to be explored, their general association is widely discussed. Risk attitude is proved to be affected by three groups of factors, natural or social environment, one's cognitive skills, and personality traits.

Existing papers proved that, among these three groups of factors, personality traits explain majority of risk preference. By using Big Five personality trait measures, many papers provided empirical evidence that openness to experiences and extraversion is positively associated with risk preference, while conscientiousness and agreeableness have the negative relationship. Under other measurement of personality, impulsive sensation-seeking is also closely related to the risk attitude. Compared to personality traits, environment and cognitive skills are only weakly related to one's risk attitude. Therefore, we view risk attitude as a mapping of various personality traits.

Heckman et al. (2008) and other scholars found that personality traits are relatively stable across lifetime and conditions. Along one's life cycle, though these traits evolve overtime, they change and fluctuate drastically during the childhood and adolescence, while having a relatively flatter evolving curve during the adulthood because of the personality maturity and emotional stability. Acting as a nature counterpart of personality, risk attitude is also relatively stable across one's life-cycle, proved by the empirical evidence.

Some papers directly investigated the stability of risk preference across time, domains, and situations. They find that as individuals grow older, they become more risk averse, and their risk preferences converge to those of adults gradually during adolescence. This finding is in line with a standard model of skill formation. From the stage of adulthood to old age, the trend to greater risk aversion continues but is less pronounced. Though the sudden shocks in some risk domains, such as the sudden death of family member, shift risk attitude to some extent, the magnitude is comparatively small to its mean-level. Temporary variations in risk preference may also exist in terms of emotion swings and short-run environmental changes.However, they only deviate risk preference from the "baseline level of risk attitude" in the short-run with small magnitude, so the risk attitude curve shows a mean-reversion pattern.

The market perception parameter, π, is determined by two major factors, objective market condition and individual's risk perception. The former is given by external situation. The latter refers to one's subjective judgement about potential risks or outcome uncertainty in different domains. Therefore, risk perception deviates one individual's perceptive risk from its actual level, and it is closely related to the human capital factors.

Many papers pointed out that the formation and change of risk perception mainly have two dimensions, which are cognitive and emotion/personality dimensions. Cognitive skills relate to how an individual know and understand the risk, while the latter relates to how one feel about it. From the cognitive aspect, self-efficacy (reasoning skills) will influence the evaluation accuracy on risk. As to personality aspect, papers proved that Big Five personality traits all closely related to how people feel about the risks. For instance, openness, extraversion, and emotional stability (neuroticism) ease one's fear of risk, leading to lower risk perception. Like risk attitude, the risk perception largely depends on one's human capital (cognitive skills and non-cognitive traits), so it is relatively stable across life cycle and external shocks after entering the adulthood.

The risk attitude and perception are potentially affected by a same group of personality traits, so they are association to each other. Though opinions in papers are inconsistent, majority has the following conclusion. When facing risky situation, risk takers tend to recognize and weigh positive outcomes. Those who have strong willingness to take risk focus more on the potential benefits, and thus have lower risk-perception scores. In contrast, risk avoiders pay too much attention to the negative consequences and tend to overestimate the possibility of potential threats and losses, resulting in biased risk perception.

In next section, we discuss in detail how we measure above parameters related to human capital with using the survey questions, and what personality traits they may reflect.

4.3 Data Resources and Variable Selection

We use China Urban Household Consumer Finance Survey 2012 (CUHCFS 2012) as the main database.[4] This round of survey is collected online, including 3,122 effective urban samples from 24 cities in China.

Among these samples, some investors may not be profit-driven, but trading for the purpose of entertainment. Entertainment-driven investors care less about the potential loss, so they have higher participation propensity but shallower participation depth. The influencing mechanism of human capital for these two types of investors thus should be different. In this paper, we mainly focus on the profit-driven investors. We assume that retired persons have more leisure time and personal wealth, so they have higher chance to

[4] CUHCFS has four rounds of surveys (2008, 2010, 2011 and 2012). However, only the last round has the questions related to financial knowledge and personality traits, so we only use CUHCFS 2012.

be entertainment-driven. Therefore, we drop the retired samples with males above 60 years old and females above 55.

Moreover, outliers in household assets (higher than 10 million RMB) and monthly income (higher than 30 thousand RMB) are also chopped, because they might also be the entertainment-driven investors with different investment strategies. We also remove the samples without wage income, because they are either full-time investors trading as their career, or unemployed person with sparse money to invest. After doing the sample selection, we drop 95 households and keep 3,027 effective samples, retaining 97% of the original records.

4.3.1 Risk Attitude in General Domain

As mentioned, some demographic characteristics, such as gender and age, may reflect the general risk attitude to some extent, but they are the measures for compound human capital. To extract the pure effect of risk attitude in general domain, one of the widely used proxies is "test-based" risk attitude. It is measured by the magnitude of risk premium an individual is willing to pay in general. In CUHCFS 2012, it is reflected by the answer to a lottery game "you can either directly take a reward equal to your annual income, or play a lottery to win twice the income or get nothing. What is the required probability of winning this game?". We adopt it as the baseline proxy because it is relatively more objective and less likely to be affected by personal behaviors or environmental changes compared to other measures in CUHCFS 2012. We do not directly adopt the continuous "required probability" due to the potential problem of nonlinear impact. Instead, we use the probability of 55% as a cutoff to create a dummy, classifying respondents into risk-averse and risk-loving groups.[5] Based on the descriptive statistics (Table 4.1), 44.6% of the respondents are risk averse under this criterion.

However, this measure has disadvantages. The respondents need to calculate the ex-

[5] Most people tend to be risk averse, so using 55% can better distinguish the risk-averse person from the risk-preferred ones. We also try 60%, and the results are robust (36.96% report a risk-averse attitude).

Table 4.1: Definition and Descriptive Statistics of Personality traits

Variables	N	Mean	Std.	Max	Min
General Risk Attitude					
Test-based	3027	0.4460	0.4972	1	0
Self-reported Financial Risk Attitude					
Risk Averse	3027	0.2696	0.4438	1	0
Risk Neutral	3027	0.4024	0.4905	1	0
Risk Loving	3027	0.3280	0.4696	1	0
Combined General RA	3027	0.4979	0.5001	1	0
Debt Tolerance (low)	2756	0.4013	0.4903	1	0

pected return and estimate a tolerable risk premium, so this measure turns out to be a mix effect of the actual risk attitude and numeracy skill. Besides this measurement error, respondents might also "randomly" give an expected probability rather than calculating it earnestly. Therefore, the test-based proxy has the measurement error due to the evaluation and report bias. Finally, it reflects one's risk attitude in general, but tells little information in other facets, such as finance.

To address the severity of measurement error, we try to fix it by using a second proxy in different risk attitude fact.[6] Risk attitude in finance facet is directly reflected by the self-reported tolerance towards financial uncertainty. In CUHCFS 2012, answers to "which kind of investment would you prefer?" are classified into five levels, from "high return high risk" to "don't want to take any risk". For simplicity, we classify these five levels into three categories, which are risk-loving (high risk or relatively high risk), risk-neutral (moderate risk) and risk-averse (low risk or no risk). Based on the descriptive statistics (Table 4.1), 26.96% of the household heads are risk-loving, 40.24% are risk-neutral, and the remaining 32.8% are risk-loving.

We find a severe mismatch that only 1,644 respondents (54.31% of entire sample) have the consistent answers towards test-based and self-report questions. Therefore, we use two

[6] If one is risk-neutral in self-reported measure, we give it tolerance to match with either risk-loving or risk-averse in test-based measure.

strategies to address this issue. First, we only use "matched samples" at a cost of losing significant number of samples. Among matched samples, risk-averse persons account for 44.83% and the remaining 55.17% are risk-loving. Another method is using test-based proxy in general domain as the base, and filling mismatched samples with risk attitude in finance facet, because the mismatch mainly comes from the arbitrary answers to the "lottery game". The advantage is that it minimizes the measurement error by keeping all effective samples. In Table 4.1, the descriptive statistics show that 49.79% are risk-averse and 50.21% are risk-loving in this new measure.

4.3.2 Debt Tolerance - Financial Risk Attitude

In CUHCFS 2012, debt attitude is reflected by the highest tolerance level towards the debt, measured in times of a household's annual income. Due to its self-reported nature, debt tolerance is a mixture of the vulnerability of family's financing, household head's ability to manage assets, and most importantly, his/her personality traits.[7] Financial integrity depends on the nature of household's assets and incomes. Stable income (wage income, etc.) and low-risk assets (treasury bill, bank deposits, etc.) reduce the financing vulnerability when facing sudden shocks, and thus a family can manage and tolerate more debts.

Besides the objective factors, debt tolerance is also influenced by the human capital factors. From the aspect of cognitive skills, the financing stability is also influenced by household head's ability to manage assets, including financial literacy and cognitive skills. Those who have higher financial efficacy and reasoning skills possess a better sense and stronger capacity to manage the household wealth well, so expecting a higher expected returns from risky financing.

Most importantly, debt tolerance reflects one's non-cognitive personality. From the aspect of personality traits, debt tolerance first works as a proxy for one's risk attitude. Unlike the "test-based" measure in the last sub-section which reflects the risk attitude in the

[7] We do the estimation by regressing debt tolerance on all the objective and subjective factors mentioned below, all getting significant results.

general domain, debt tolerance is more related to one's attitude towards financial market and financial vulnerability. It thus measures household head's risk attitude in the finance facet.[8] Comparing these two proxies, the general risk attitude is relatively stable with gradual evolution and little fluctuation across lifetime, while the financial one is more sensitive toward external shocks in short run, especially the market turbulence. The correlation coefficient between risk attitudes in general and finance domain is only 0.06, giving very weak association. Therefore, they measure risk attitudes from different aspects and time frames with neglectable multicollinearity.

Besides risk attitude, debt tolerance also reflects other personality traits. For instance, due to the self-reported nature, self-confidence and trust attitude may also influence debt tolerance. First, the less-confident persons prefer to use in-hand assets to finance household wealth rather than seeking for external debt, so they have lower debt tolerance. Moreover, when reporting debt tolerance, they potentially overestimate their own financial efficacy and underestimate financial risk, so having better perspective towards debt health. For trust attitude, those who trust more on the market and external information, are more tolerant to the debt payable.

To measure debt tolerance, "how many times of the annual income" may have a non-linear impact on risky investment. For instance, the impact of jumping from 1 to 2 times may not be the same as that of changing from 8 to 9 times. This "self-report" measure also depends on the self-evaluation, so it is not perfectly comparable across individuals. Therefore, we create a dummy to classify high and low debt tolerance by setting a proper cutoff. In existing papers using U.S. data, "highest bank loan an individual can get" is a widely used and preferable cutoff. Unfortunately, there is no clear ceiling for bank loan in China, which is bank- and customer-specific. However, most family can get a bank loan around 30 times of their monthly income, so we use three times the annual income as the cutoff. Based on descriptive statistics (Table 4.1), the original measure is left-skewed with

[8] Though we have a direct "self-reported" proxy for financial risk attitude mentioned in last sub-section, it is too straightforward, directly inferring one's financial behavior, so we adopt debt tolerance instead.

an average value of 4.1 times and largest value of 12 times. More than 54.7% households can only handle a low level of debt, which is less than 3 times the annual income.

4.3.3 Dependent Variables - Financial Behaviors

For financial behavior, we mainly focus on the participation propensity of stocks, because stocks are the most accessible risky product in China. We use "whether a household holds stock accounts" as the proxy for the long-run stock investment propensity. Besides the participation decision, we also discuss the participation depth, measured by the proportion of household wealth allocated to stocks. It also partially addresses the "inactive trading" issue in account-holding measure.[9] However, the investment depth measure potentially bears the measurement or reporting bias, and the high-frequency trading behavior may further lead to its large fluctuation in the short-run.[10] Therefore, we need to treat these results dialectically, explaining them jointly with that of the "account-holding dummy".

We also consider the participation propensity and depth of an alternative product, which is mutual fund. It is a portfolio of various risky and less-risky products, carefully selected, bundled and sold by financial agents. Due to the diversification, the idiosyncratic risk of these products may hedge each other, so mutual fund has relatively lower risk than stock though it is still risky product. By considering both stocks and funds, we can compare the different impacts of human capital on financial products with different level of risk.

Based on the descriptive statistics (Table 4.2), around 40.27% and 38.2% of the households have stock and fund accounts respectively. Among those who invest in stocks, 87.1 thousand RMB are allocated to stocks, equivalent to 4.98% of the household wealth. The magnitude for mutual fund is around 49.8 thousand RMB, equivalent to 3.96% of family assets. Compared to the developed countries, the participation rate in China is much lower than that of United States. The same for the investment proportion that U.S. residents

[9] Some investors do not trade actively even if they have accounts, so "account holding" might be biased.

[10] It is hard to precisely report the exact amount invest in stocks. However, we assume this bias is randomly distributed across households, so we simply ignore its impact.

allocates 14% of their assets on stock, which is much higher than that in China.

Table 4.2: Definition and Descriptive Statistics of risky investment

Variables	**N**	**Mean**	**Std.**	**Max**	**Min**
Stock (Dummy)	3027	0.4027	0.4905	1	0
Fund_(Dummy)	3027	0.3822	0.4860	1	0
Stock (Proportion)					
Full Samples	3027	2.005	3.969	46.15	0
Invested Samples	1219	4.978	4.932	46.15	0.134
Fund (Proportion)					
Full Samples	3027	1.515	4.461	57.47	0
Invested Samples	1157	3.963	6.511	57.47	0.105

4.3.4 Control Variables

For household heads, we consider their age, gender, education, and marital status, because they indirectly reflect the compound human capital. For instance, older or female individuals are more risk averse in nature, so they have lower incentive to purchase risky assets. These controls may also be the proxy for cognitive ability, such as logical thinking and reasoning, influencing market prediction accuracy. Marital status may also shift one's incentives to invest.

For household factors, family composition, especially the number of dependent children and elders, has a significant impact on financial behaviors. Higher burden to support kids or elders creates incentive to accumulate assets faster via risky investment, but larger uncertainty motivates household to choose stable strategies. For financial condition, family with more wealth and stable income are more capable to bear the investment failure with higher risk tolerance. Living in big city benefits more from the advanced financial market but also face the more severe financial constraints due to a higher living burden.

Based on statistics (Table 4.3), 71.4% of the household heads are males, and 84% are married. 56.5% do not have any dependent kids, following by "one-child" (38.7%).[11] Most

[11] The dependent children are defined as the preschool and school-age kids.

households do not have elders to support (77.5%), but around 10% still have more than one elders. The income distribution is left-skewed with 12.8% high-income, 27.1% middle-income and 60% low-income households. The average household wealth is 1.67 million RMB, and around 22% of the families live in big cities.[12] Compared to other household surveys in China, CUHCFS 2012 has the much younger and highly educated household heads, with an average age of 33.9 and 87.7% college or higher degree owners. One possible explanation is that CUHCFS 2012 was collected online for the urban households, so some respondents with certain characteristics are excluded. Therefore, we need to explain the results carefully because they are only applicable for specific samples.

Table 4.3: Definition and Descriptive Statistics of control variables

Variables	**N**	**Mean**	**Std**	**Max**	**Min**
Age	3027	33.95	7.127	60	25
Gender	3027	0.7139	0.452	1	0
Education (college or above)	3027	0.8788	0.3265	1	0
Marriage	3027	0.8401	0.3666	1	0
Number of Elders	3027	0.3244	0.6533	4	0
Number of Kids	3027	0.4876	0.6030	5	0
Family Total Assets	3027	167.1	141.4	981.8	1.4
Family Income (Monthly)					
Low (<10000)	3027	0.6013	0.4897	1	0
Middle (10000-20000)	3027	0.2712	0.4447	1	0
High (>20000)	3027	0.1275	0.3336	1	0
Geographic Location					
Beijing/Shanghai/Guangzhou	3027	0.2197	0.4141	1	0
Capital Cities in Provinces	3027	0.4414	0.4966	1	0
Other Cities	3027	0.3389	0.4734	1	0

Note: "Family total assets" is measured in 10 thousand RMB.

[12] Big city is defined as Beijing, Shanghai, and Guangzhou.

4.4 Participation Decision on Stocks and Funds

4.4.1 Participation Decision in a Long-run Framework

We first explore the impacts of two measures for risk attitude on participation propensity. $stock_i$ is the stock investment decision, measured by "whether hold stock accounts", which is a propensity measure in a long-run frame. HC_i includes the "test-based" risk attitude and debt tolerance of the household heads. X_i is a vector of household and household head's controls. ε_i is the idiosyncratic error.

This participation decision is a binary variable, so we adopt Probit model to estimate. A latent variable, $stock_i^*$, in a general model specification can be constructed as:

$$stock_i^* = \alpha_1 HC_i + \alpha_2 X_i + \varepsilon_i$$

Therefore, the binary stock participation decision can be viewed as an indicator of whether latent variable $stock_i^*$ is positive:

$$stock_i = \mathit{1}\left[stock_i^* > 0 | HC_i, X_i\right] = \begin{cases} 1, & if stock_i^* > 0. \\ 0, & otherwise. \end{cases} \tag{4.10}$$

To implement the Probit method, we investigate general risk attitude and debt tolerance in a sequential manner, adding them gradually into the model and then include both. According to the pseudo R^2, personality traits have strong explanatory power in the variation of participation propensity (Table 4.4). When only controlling for household and its head's general factors, Probit estimation gives a pseudo R^2 of 14.11%, while the explanation power increases to 17.36% or 15.16% after controlling for general risk attitude and debt tolerance, respectively. After including both factors, pseudo R^2 raises to 18.5%, indicating that personality traits play important roles in participation decision and should be isolated from the unobserved error term.

Based on the results, those who are generally risk averse, have 18.2% lower possibility

Table 4.4: Stock Participation Decision (Probit Estimation)

	Full Samples				Matched Samples	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk_averse		-0.1815***		-0.1802***	-0.1332***	-0.1342***
		(0.0149)		(0.0154)	(0.0215)	(0.0223)
Debt_rolerance			-0.0434**	-0.0385**		-0.0402
			(0.0185)	(0.0180)		(0.0254)
Age	-0.0021*	-0.0014	-0.0015	-0.0006	-0.0016	-0.0004
	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0018)	(0.0018)
Gender	0.0294	0.0228	0.0310*	0.0254	0.0041	0.0107
	(0.0181)	(0.0176)	(0.0187)	(0.0183)	(0.0236)	(0.0246)
Education	0.0954***	0.0813***	0.0922***	0.0769***	0.0983**	0.0910**
	(0.0275)	(0.0269)	(0.0277)	(0.0271)	(0.0391)	(0.0390)
Marriage	0.0249	0.0209	0.0182	0.016	0.0586*	0.0478
	(0.0257)	(0.0248)	(0.0266)	(0.0257)	(0.0337)	(0.0352)
Num. of kids	0.0402***	0.0415***	0.0381***	0.0415***	0.0594***	0.0493***
	(0.0128)	(0.0125)	(0.0135)	(0.0131)	(0.0166)	(0.0176)
Num. of elders	0.1050***	0.0979***	0.1120***	0.1053***	0.0995***	0.1092***
	(0.0167)	(0.0158)	(0.0176)	(0.0167)	(0.0229)	(0.0239)
ln(asset)	0.1486***	0.1363***	0.1505***	0.1369***	0.1379***	0.1370***
	(0.0107)	(0.0105)	(0.0110)	(0.0107)	(0.0150)	(0.0155)
Middle_income	0.1080***	0.1022***	0.1057***	0.0961***	0.1156***	0.1131***
	(0.0198)	(0.0193)	(0.0228)	(0.0221)	(0.0267)	(0.0305)
High_income	0.0396	0.0395	0.0155	0.0174	0.0576	0.0395
	(0.0270)	(0.0263)	(0.0277)	(0.0270)	(0.0362)	(0.0375)
Big_city	-0.0524**	-0.0511**	-0.0556***	-0.0532**	-0.0252	-0.0256
	(0.0206)	(0.0200)	(0.0216)	(0.0209)	(0.0277)	(0.0291)
Observation	3027	3027	2756	2756	1644	1488
Pseudo R^2	0.1411	0.1736	0.1516	0.1847	0.1637	0.1720

Note:

1. We report the marginal effect;
2. The significance level: ***0.01, **0.05, *0.1.

of stock purchasing compared to risk-loving respondents. Low-debt-tolerant persons have 4.3% lower stock investment incentives. Adding them both into the model, the estimates reduce slightly to 18% and 3.9% respectively, while they are still significant. The results imply that risk aversion in general and finance domains both prevent people from participating in stock market. Since they measure different facets of risk attitude, including them both in the model still gives significant impacts. Moreover, debt tolerance also reflects other personality traits, verified by the significant estimate after controlling general risk attitude.

As to household heads' demographic factors, olders are reluctant in purchasing stocks, while males and college-education ones have higher incentive to participate. However, after controlling general risk attitude and debt tolerance, the significance of age and gender is gone, and marginal effect of college education reduces though its impact still significant. One possible reason is that they potentially reflect the heterogeneity in cognitive skills and personality across different cohorts. Therefore, after controlling for the proxies of personality and cognition, individuals in different age, gender and education are indifferent in making risky investment decision.

For other controls, richer households are more willing to purchase stocks due to sufficient financial supports to bear the failure risk. Middle-income families have the highest participation incentives. Possible reason is that low-income families lack stable financial sources, and high-income families prefer other investment methods, so they have lower incentives to buy stocks. Household with more kids or elders has significantly higher incentive to purchase stocks. Those who live in big cities are reluctant to hold stock due to high living burden with less spare money.

We also check the impacts of personality traits on fund participation. Fund is an alternative product in the class of risky assets with a lower risk. General risk attitude and debt tolerance also have notably impacts on fund purchasing (Table 4.5). Risk aversion in general and finance domains reduce fund purchasing probability by 11.9% and 6%, respectively. The results indicate that even after we control for the long-run propensity in fund

Table 4.5: Fund Participation Decision (Probit Estimation)

	Full Samples				Matched Samples	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk_averse		-0.1191***		-0.1139***	-0.0659***	-0.0699***
		(0.0162)		(0.0169)	(0.0230)	(0.0240)
Debt_tolerance			-0.0603***	-0.0565***		-0.0182
			(0.0190)	(0.0188)		(0.0266)
Age	-0.0023*	-0.0018	-0.0018	-0.0013	-0.0006	-0.0002
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0018)	(0.0019)
Gender	0.0011	-0.0030	-0.0044	-0.0080	-0.0131	-0.0177
	(0.0186)	(0.0184)	(0.0193)	(0.0191)	(0.0249)	(0.0260)
Education	0.0895***	0.0813***	0.0870***	0.0783***	0.0682*	0.0596
	(0.0281)	(0.0278)	(0.0283)	(0.0280)	(0.0399)	(0.0398)
Marriage	0.0121	0.0103	0.0076	0.0066	0.0306	0.0329
	(0.0260)	(0.0256)	(0.0269)	(0.0265)	(0.0353)	(0.0369)
Num. of kids	0.0607***	0.0611***	0.0529***	0.0545***	0.0799***	0.0816***
	(0.0132)	(0.0130)	(0.0140)	(0.0138)	(0.0175)	(0.0186)
Num. of elders	0.0833***	0.0787***	0.1044***	0.1002***	0.0846***	0.0951***
	(0.0167)	(0.0164)	(0.0175)	(0.0172)	(0.0233)	(0.0247)
ln(asset)	0.0911***	0.0833***	0.0846***	0.0765***	0.0920***	0.0831***
	(0.0109)	(0.0108)	(0.0110)	(0.0110)	(0.0155)	(0.0159)
Middle_income	0.0471**	0.0441**	0.018	0.0134	0.0254	0.0104
	(0.0209)	(0.0207)	(0.0241)	(0.0239)	(0.0286)	(0.0328)
High_income	0.1156***	0.1157***	0.0859***	0.0876***	0.1238***	0.1180***
	(0.0278)	(0.0275)	(0.0285)	(0.0282)	(0.0381)	(0.0395)
Big_city	-0.0097	-0.0087	-0.0052	-0.0037	-0.0119	-0.0125
	(0.0211)	(0.0209)	(0.0221)	(0.0219)	(0.0291)	(0.0308)
Observation	3027	3027	2756	2756	1644	1488
Pseudo R^2	0.0857	0.0984	0.0936	0.1055	0.0934	0.0984

Note:

1. We report the marginal effect;
2. The significance level: ***0.01, **0.05, *0.1.

investment determined by the general risk attitude, risk aversion in finance facet further reduces the probability of purchasing fund by 6% more. In contrast, the magnitude of general risk attitude is smaller than that in stock purchasing, because risk averse persons are more sensitive to riskier products, such as stocks.

Elder has lower incentives in fund purchasing before controlling for any direct measures of personality traits. Every one-year older increases the probability of fund investment by 0.23%. College education significantly motivates persons to invest in fund with 8.9% higher possibility. The same as the stock investment, the significance of age is gone, and the magnitude of college education shrinks after controlling for the pure effects of personality traits. These results indicate that demographic characteristics influence risky asset investment mainly through the channel of human capital, especially the personality traits. Unlike the stock investment, among three income categories, high-income households have the highest propensity to purchase funds. One possible reason is that the marginal utility gained via risky investment is smaller for high-income households. Therefore, they have lower motivation to allocate assets on the riskier products, but prefer to invest in the less risky instead, such as funds, to gain reasonable returns. People in big cities is not necessarily to have lower incentives in fund purchasing, because funds are relatively safer with decent returns.

4.4.2 Instantaneous Participation Decision

As mentioned, account-holding dummy reflects the participation propensity in a long-run frame, implying a general attitude towards risky investment. However, it potentially has the issue of "inactive trading" and does not reflect how an individual with specific human capital reacts to the market turbulence during certain period. Thus, we further use "the proportion of household assets allocated to stocks/funds" as the supplement to partially address this issue and explain the impacts of human capital on instantaneous decision.

The dependent variable, stock proportion in percent point, is censored with $stock\_p_i \in$

$[0, 100]$. Around half of the respondents who meet certain criterion has $stock\_p_i = 0$, while others have $stock\_p_i \in (0, 100]$. Therefore, we use Tobit method to estimate, and provide a marginal effect of participation decision. We define a latent or uncensored stock proportion, $stock\_p_i^*$, which is the true value of $stock\_p_i$ when the censoring mechanism is not applied:

$$stock\_p_i^* = \rho_1 HC_i + \rho_2 X_i + \mu_i$$

Therefore, the marginal probability is:

$$P(stock\_p_i > 0 | HC_i, X_i) = P(stock\_p_i^* > 0 | HC_i, X_i) \tag{4.11}$$

Based on the results, the significance of debt tolerance is gone with smaller magnitude, but the direction is the same (Table 4.6). Due to a bad stock market condition during 2011-2012, some investors, especially those who are more debt-tolerant or less risk averse in finance facet, choose to take a wait-and-see strategy in the short-run. Though they are still willing to participate in the risky investment, other risky products are better alternatives. Therefore, persons with different debt tolerance level are comparatively indifferent in stock purchasing with the reluctant attitude. In the long-run, those who are financially risk-loving are still interested in stock investment, so account-holding dummy significantly reacts to the financial risk attitude. Unlike debt tolerance, no matter how the market condition changes, the persons who are risk averse in general tend to avoid the risky investment with 18% lower probability of stock participation. Above results indicate that risk aversion in finance domain is more sensitive to the market change compared to risk attitude in a general sense, which is intuitively reasonable.

Other variables are relatively consistent, except for number of dependent children. Families with more kids have higher incentives of risky investment, aiming at accumulating family wealth quicker to support their kids in the long run. However, if facing a short-run downturn condition, they prefer to temporarily leave the market, to avoid the potential drastic turbulence in household financial condition. Unlike dependent kids, elders are not

Table 4.6: Tobit Estimation - Marginal Effect on Participation Decision

	Stocks			Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
Risk_averse		-0.1797***	-0.1131***		-0.0850***	-0.0710***
		(0.0149)	(0.0222)		(0.0160)	(0.0226)
Debt_tolerance		-0.0243	-0.0243		-0.0514***	-0.0220
		(0.0178)	(0.0256)		(0.0185)	(0.0265)
Age	0.0001	0.0013	0.0017	-0.0027**	-0.0021*	-0.0017
	(0.0012)	(0.0013)	(0.0019)	(0.0011)	(0.0012)	(0.0017)
Gender	0.0147	0.0135	0.0107	-0.0079	-0.013	-0.0077
	(0.0176)	(0.0179)	(0.0235)	(0.0176)	(0.0181)	(0.0241)
Education	0.1062***	0.0872***	0.1079***	0.0569*	0.0489	0.0113
	(0.0291)	(0.0285)	(0.0394)	(0.0334)	(0.0331)	(0.0485)
Marriage	0.0189	0.0104	0.0616*	0.0085	0.0005	-0.0026
	(0.0261)	(0.0262)	(0.0328)	(0.0267)	(0.0275)	(0.0405)
Num. of kids	0.0177*	0.0157	0.0237*	0.0348***	0.0315***	0.0422***
	(0.0099)	(0.0102)	(0.0142)	(0.0093)	(0.0098)	(0.0126)
Num. of elders	0.0877***	0.0910***	0.0773***	0.0539***	0.0654***	0.0671***
	(0.0147)	(0.0149)	(0.0196)	(0.0127)	(0.0129)	(0.0182)
ln(asset)	0.0785***	0.0677***	0.0683***	-0.0258**	-0.0332***	-0.0436***
	(0.0116)	(0.0117)	(0.0170)	(0.0114)	(0.0113)	(0.0164)
Middle_income	0.0821***	0.0713***	0.0886***	0.0412**	0.0127	0.0034
	(0.0184)	(0.0199)	(0.0287)	(0.0166)	(0.0191)	(0.0267)
High_income	0.0374*	0.0186	0.0544	0.1182***	0.0910***	0.1240***
	(0.0227)	(0.0226)	(0.0335)	(0.0215)	(0.0221)	(0.0324)
Big_city	-0.0437**	-0.0411**	-0.0333	0.0346*	0.0421**	0.0393
	(0.0191)	(0.0195)	(0.0257)	(0.0200)	(0.0208)	(0.0294)
Observation	3027	2756	1488	3027	2756	1488
Pseudo R^2	0.0277	0.0447	0.0351	0.0095	0.0148	0.0125

Note:

1. We report the marginal effect for participation decision, which is $P(inv\_p_i > 0|HC_i, X_i)$;
2. Column (3) and (6) report the results with sub-samples (matched samples in general risk averse);
3. The significance level: ***0.01, **0.05, *0.1.

necessarily to be supported, especially in Chinese urban households with high education. Based on Chinese tradition, elders accumulate more wealth and provide more financial supports to their next generation, rather than receiving support from kids. This tradition encourages risky investment in both long- and short-run with insensitive reaction to market turbulence, even though its impact is relatively smaller when the market condition is poor. Wealthy or middle-income households still have higher incentives to purchase stocks in the short run, with lower motivation in downturn market condition.

We also check the instantaneous participation decision on funds (Table 4.6). Unlike the stock market, fund market is relatively stable in 2011-2012, so most results are consistent with those in the long-run perspective. Risk averse persons in general are still reluctant to purchase funds, with 8.5% lower participation probability. Individuals who are less tolerant to debt, reflecting a lower risk tolerance in finance domain, have significantly weaker incentives to invest in funds, with a comparable magnitude of 5.1%.

Other interesting findings include that those who live in the big cities are more willing to purchase funds if using "zero-investment amount" as the measure of participation decision. To explain it, when the stock market experienced a downturn, funds act as the preferred alternative risky assets with higher return than risk-free assets, so these investors would shift to fund market to secure wealth. Though well-educated persons generally have higher incentives to participate in fund market, they are not necessarily actively trading the fund with an insignificant impact.

Comparing above results with those of stocks across two different participation measures, we find that the impacts of human capital factors on the participation decision in risky assets are sensitive to market condition and risk level of the products. Risk attitude in both domains is more sensitive to the riskier products, reflecting by a larger magnitude in stock participation. However, when facing a severe market condition, investors with certain personality traits are more reactive to market turbulence, especially for the riskier assets. For instance, financial risk attitude is more sensitive to market change than risk preference in general sense. Those who are financially risk-loving change their attitude in stock investment when the market condition is poor, leading to an insignificant estimate. In contrast, risk attitude in general facet reflects one's long run preference, so it has consistent impact on risky investment regardless the market condition, especially when the financial risk attitude is controlled. For other objective factors, such as household's financial condition, they react relatively insensitive to market change, implying that preference factors are the main drive-force of strategical change to market turbulence.

4.5 Investment Depth on Stocks and Funds

Not only the stock/fund participation propensity, but also the investment depth is affected by the human capital factors. As mentioned, participation depth is censored with $stock\_p_i = 0$ when certain criteria are reached, while others would invest $stock\_p_i \in (0, 100]$. Therefore, we use Tobit model to get the marginal effect on investment depth conditional on participation.

This uncensored value, $stock\_p_i^*$, is assumed to have a normal distribution, and $stock\_p_i$ is assigned the value based on following criteria:

$$stock\_p_i = max(stock\_p_i^*\ ,\ 0) = \begin{cases} stock\_p_i^*, & if\ stock\_p_i^* 0. \\ 0, & if\ stock\_p_i^* < 0. \end{cases} \tag{4.12}$$

After implementing the Tobit model, we find that people with different age and gender are indifferent in stock investment depth (Table 4.7, Column 1 and 2). Risk averse persons in general facet allocate 1.47 percent point less assets on stocks. Compared with the mean level of stock proportion, which is 2%, this magnitude is huge, and equivalent to 73.5%. Financial risk attitude, measured by debt tolerance, is more sensitive towards market turbulence. Those who are financially risk-averse are not distinguished from risk-loving persons when face downturn market condition. It is rational for financially risk-loving investors

Table 4.7: Tobit Estimation - Marginal Effect on Participation Depth

	Stocks			Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
Risk_averse		-1.4698***	-0.9058***		-0.6978***	-0.6262***
		(0.1463)	(0.1871)		(0.1362)	(0.2065)
Debt_tolerance		-0.1992	-0.1945		-0.4223***	-0.1942
		(0.1447)	(0.2042)		(0.1529)	(0.2346)
Age	0.0008	0.0110	0.0134	-0.0217**	-0.0168*	-0.0146
	(0.0100)	(0.0105)	(0.0151)	(0.0090)	(0.0097)	(0.0148)
Gender	0.1182	0.1107	0.0853	-0.0624	-0.1064	-0.0676
	(0.1413)	(0.1463)	(0.1885)	(0.1393)	(0.1492)	(0.2121)
Education	0.8538***	0.7134***	0.8639***	0.4492*	0.4012	0.0997
	(0.2359)	(0.2345)	(0.3237)	(0.2611)	(0.2686)	(0.4262)
Marriage	0.1523	0.0848	0.4933*	0.0672	0.0043	-0.0229
	(0.2094)	(0.2142)	(0.2672)	(0.2109)	(0.2256)	(0.3571)
Num. of kids	0.1423*	0.1287	0.1895*	0.2751***	0.2589***	0.3727***
	(0.0794)	(0.0832)	(0.1134)	(0.0748)	(0.0815)	(0.1131)
Num. of elders	0.7055***	0.7448***	0.6194***	0.4257***	0.5370***	0.5923***
	(0.1247)	(0.1294)	(0.1580)	(0.1030)	(0.1113)	(0.1714)
ln(asset)	0.6312***	0.5541***	0.5473***	-0.2039**	-0.2725***	-0.3844**
	(0.0850)	(0.0873)	(0.1271)	(0.0985)	(0.1042)	(0.1664)
Middle_income	0.6604***	0.5829***	0.7093***	0.3257**	0.1042	0.0300
	(0.1478)	(0.1633)	(0.2346)	(0.1315)	(0.1569)	(0.2355)
High_income	0.3007*	0.1522	0.4358	0.9340***	0.7467***	1.0939***
	(0.1826)	(0.1855)	(0.2715)	(0.1807)	(0.1903)	(0.2988)
Big_city	-0.3512**	-0.3359**	-0.2670	0.2732*	0.3460*	0.3470
	(0.1528)	(0.1586)	(0.2064)	(0.1632)	(0.1769)	(0.2677)
Observation	3027	2756	1488	3027	2756	1488
Pseudo R^2	0.0277	0.0447	0.0351	0.0095	0.0148	0.0125

Note:

1. We report the marginal effect for participation depth: $E(inv\_p_i^*|inv\_p_i > 0)$;
2. Column (3) and (6) report the results with sub-samples (matched samples in general risk averse);
3. The significance level: ***0.01, **0.05, *0.1.

to take wait-and-see strategy, placing fixed amount of assets on stocks but allocating more wealth on other alternative products in better condition. Though total investment on risky assets is larger for financially risk-loving investors, the fraction that allocated to stocks is not necessarily to be higher than financially risk-averse people.

Compared the impacts on stock participation propensity and depth with the same dependent variable, the results are relatively consistent.[13] Those who are generally risk averse not only have inactive trading behavior with lower incentives, but also allocate less assets on stocks when face market change. Both participation decision and depth are insignificantly influenced by financial risk attitude, measured by the debt tolerance. With the similar explanation mentioned before, insignificant impact of debt tolerance potentially comes from the sensitive reaction of financially risk-averse persons towards the market turbulence.

We also check how these two personality factors influence the depth of fund investment in a stable market condition. Based on the results (Table 4.7, Column 4 and 5), their impacts on funds and stocks are similar. Those who are generally risk averse tend to allocate 0.7% less assets on funds, equivalent to 17.7% of its average level. This magnitude is relatively smaller compared to that of stocks. In accord with our expectation, risk aversion in finance also influences the fund investment depth in a negative direction. Lower level of debt tolerance potentially discourages investors to allocate larger proportion of wealth on risky products, with the magnitude of 0.42%. Under severe condition, as an alternative way of risky investment, funds absorbed even more household assets from stocks, especially for those who are financially risk averse, so this impact is potentially magnified.

For other composited human capital measures, as getting older, one tends to allocate more assets on stocks but less on funds, though the magnitude of its impact is marginal. One possible explanation is that young persons are more vulnerable due to the unstable income and high living burden, and have sparse time to manage stocks. Males prefer to allocate more wealth on riskier products which require more knowledge and stronger skills,

[13] The results are robust with marginal magnitude changes when we only use the matched sample.

while allocate less assets on funds with lower risk. Persons with high level of formal education are more capable in handling riskier products due to stronger cognitive skills, richer knowledge, and more confidence, reflected by a larger amount of stock investment. However, due to the "pre-packaged" nature, funds only require lower trading skills, so the assets allocated to funds is indifferent across persons with different education level.

For other controls, family with more elders potentially have richer financial supports from them, especially in the well-educated urban family, while more kids may encourage family to seek higher returns via risky investment. Therefore, elders and kids both lead to a larger amount of stock and fund investment. Wealthy family prefers to invest more in stocks but less in funds due to the stronger financial supports to handle riskier assets. Middle-income households allocate more assets on stock due to healthier financial condition and higher utility from risky investment. However, the high-income households are not necessarily to purchase more stocks because they have lower incentives to gain marginal returns, and funds seem to be a saver product to place the assets. Due to higher living burden, households located in the big cities allocate more assets on housing property, liquid assets, or low-risk assets to meet the urgent needs in the future, instead of investing in risky assets like stocks, especially in this downturn period.

4.6 Sensitivity Test

As mentioned in the theoretical part, existing papers point out that unobservable cognitive and non-cognitive skills are relative stable. Though the personality traits evolve gradually over the lifecycle, they are sufficiently stable across special situations (Borghans et al., 2008). Cobb-Clark and Schurer (2012) examined personality change is insensitive to the adverse life-time events, which is further verified by others using different age groups and time-frame (Elkins et al., 2017). In this case, personality traits can be used as the stable inputs in economic decision, and the endogeneity issue caused by reverse or simultaneous causality is weak.

However, some may argue that omitted variables problem might exist, because we cannot control every influencing factor. The key idea of this paper is to extract unobservable personality traits from the error term by using proxies. Therefore, the omitted variable issue in the decision-making research should be addressed to a large extent. Even though, we still adopt the IV-Probit and IV-Tobit methods to further check the robustness of our results:

First stage: $$HC_i = \gamma_1 Z_i + \gamma_2 X_i + \epsilon_i \tag{4.13}$$

Second stage: $$inv_i = \alpha_1 HC_i^* + \alpha_2 X_i + \varepsilon_i \tag{4.14}$$

$$inv_{p_i} = \beta_1 HC_i^* + \beta_2 X_i + \mu_i \tag{4.15}$$

We refer to "neighborhood" strategy to select instruments Z_i (Brown et al., 2008; Robalino and Pfaff, 2012).[14] In our case, only the information of city is available, which may be a too large geographic concept for individuals to share the similar human capital features. Therefore, besides the city, we also use occupation, age, and gender to categorize respondents into different groups. We use the proportion of peers within the same group who are risk averse in general and finance facets as the instruments for these two personality traits. We drop the samples who are the sole member within the group, so sample size reduces a little bit to 2,678.

Based on the results, the estimates are robust, further supporting our baseline results. Both stock and fund participation rates react notably to general risk aversion in the long run, reducing 17.1% and 11.2%, respectively (Table 4.8, Column 1 and 2). They are also motivated by the high debt tolerance with larger and significant impact on stock participation of 7.3%. For an instantaneous measure of participation decision, risk averse persons in general facet have lower possibility of 17.4% and 8.3% to hold stocks and funds in 2012 when facing severe condition in the stock market (Table 4.8, Column 3 and 4). In contrast, the impact of financial risk attitude becomes insignificant for stock participation, while remains insignificant for funds, implying its sensitive reaction towards market change. As to

[14] These papers use the average values of endogenous variables in the neighborhood as the instruments.

Table 4.8: Endogeneity Adjustment (IV-Probit and IV-Tobit)

	Probit (Acc. Dummy)		**Tobit (Decision)**		**Tobit (Depth)**	
	Stock	Fund	Stock	Fund	Stock	Fund
Risk_averse	-0.1710***	-0.1117***	-0.1743***	-0.0829**	-1.4095***	-0.6682**
	(0.0369)	(0.0399)	(0.0355)	(0.0378)	(0.3086)	(0.3096)
Debt_tolerance	-0.0727*	-0.0630	-0.0555	-0.0509	-0.4491	-0.4101
	(0.0408)	(0.0424)	(0.0393)	(0.0404)	(0.3195)	(0.3274)
Age	-0.0007	-0.0015	0.0015	-0.0017	0.0120	-0.0138
	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0117)	(0.0121)
Gender	0.0261	-0.0122	0.0136	-0.0170	0.1101	-0.1369
	(0.0202)	(0.0212)	(0.0193)	(0.0196)	(0.1558)	(0.1583)
Education	0.0842***	0.0695**	0.0822***	0.0286	0.6651***	0.2303
	(0.0310)	(0.0317)	(0.0298)	(0.0297)	(0.2417)	(0.2391)
Marriage	0.0269	0.0062	0.0196	-0.0075	0.1585	-0.0601
	(0.0275)	(0.0286)	(0.0260)	(0.0262)	(0.2105)	(0.2107)
Num. of kids	0.0414***	0.0598***	0.0144	0.0365***	0.1168	0.2937***
	(0.0137)	(0.0145)	(0.0126)	(0.0130)	(0.1018)	(0.1050)
Num. of elders	0.1097***	0.1079***	0.0933***	0.0704***	0.7549***	0.5669***
	(0.0180)	(0.0189)	(0.0161)	(0.0167)	(0.1316)	(0.1355)
ln(asset)	0.1382***	0.0745***	0.0691***	-0.0342***	0.5590***	-0.2759***
	(0.0121)	(0.0119)	(0.0114)	(0.0108)	(0.0927)	(0.0886)
Middle_income	0.0816***	0.0103	0.0502**	0.0116	0.4064**	0.0934
	(0.0265)	(0.0283)	(0.0251)	(0.0262)	(0.2027)	(0.2106)
High_income	0.0072	0.0864***	0.0114	0.0921***	0.0918	0.7421***
	(0.0319)	(0.0332)	(0.0301)	(0.0306)	(0.2431)	(0.2467)
Big_city	-0.0418*	-0.0005	-0.0316	0.0458**	-0.2558	0.3691**
	(0.0221)	(0.0232)	(0.0204)	(0.0206)	(0.1650)	(0.1671)
Observation	2435	2435	2435	2435	2435	2435

Note:

1. We report the marginal effect;
2. The significance level: ***0.01, **0.05, *0.1.

participation depth, risk attitude in general facet significantly reduces stock and fund proportion in total wealth by 1.3% and 0.67%, respectively (Table 4.8, Column 5 and 6). The financial risk attitude has insignificant impact on the investment depth of both products, but their directions are the same with those in the baseline model. All other controls also seem to have the consistent results with baseline model, including household heads' age, gender, and education, as well as household's features.

4.7 Conclusion

In the past decades, researchers are committed to investigate the underlying mechanism of the decision-making incentives. As major participants of economic activities, households' financial behavior has long been discussed as the need of seeking solutions to regulate the market. Contributing to large body of literature, our paper explores how two domains of risk attitude influence households' investment behaviors differently. We investigate this topic at a special period, providing empirical evidence that the risk attitude, in both general and finance sense, is one of the key determinants of risky investment. The financial risk attitude reacts more sensitive towards the market change.

Our results indicate that risk averse persons in general facet not only have lower incentives to participate in stock and fund market, but also allocate less wealth on risky assets. Those who are generally risk averse have 18% and 11% lower possibilities of purchasing stocks and funds, and also allocate 1.5% and 0.7% less of their assets on them, respectively. Using three times of annual income as a cutoff to proxy for debt tolerance, those who are more risk averse in finance facet have the higher incentives to purchase both stocks and funds. Financial risk attitude also affects the participation depth of both products, but its impact is more sensitive to the market condition compared to risk attitude in general facet. This finding is supported by the evidence that high- and low- financial risk averse persons are indifferent in stock investment decision and depth in downturn condition.

For other findings, middle-income households prefer stocks to funds. In contrast, the high-income households prefer the funds with a moderate return and risk, because they potentially have lower incentives to gain marginal returns. The higher living burden and faster life pace in the large cities create motivation to purchase products with relatively stable returns, so funds are preferred. One thing needing to be mentioned is that our samples only focus on the profit-driven investors in a specific market condition. We believe that the influencing mechanism of entertainment-driven investors should be different, so further research on this topic is also valuable.

CHAPTER 5

CONCLUSION AND POLICY IMPLICATION

Besides the objective constraints and condition, human being plays a more and more important role in economy activities through decision-making and action-taking, so human capital has the prolonged impact on different aspects of national economy from individual-level to firm-level. As the important economy participants, the strategy taken by the corporations and households would largely influence the wealth accumulation, social welfare, market regulation and so on. Therefore, investigating how their human capital is accumulated, and how to precisely measure their human capital would be of great value.

Based on this framework, we did two essays on firm-level research, and one on household-level human capital. In chapter 2, we investigate how firm's executives' managerial human capital, accumulated via learning-by-doing, would influence firm's productivity. By considering the daily operation process, the executives, especially CEO and top management team (TMT), play important roles in making decision, as well as leading and implementing the strategical plans. As the results imply, CEO's special experiences significantly influence firm's production efficiency. Among all these special backgrounds, overseas and career experiences in various functions play important roles, due to their reflection of CEO's cognitive skills, management ability, personality, and so on. They either increase or reduce a firm's TFP level by 5%-10%, respectively, which is notably large in magnitude. TMT's composition is also important in terms of two potential channels. Team collaboration conflicts, measured by characteristics and experience diversity (age/tenure), significantly hinders TFP improvement. Larger proportion of females and educated members spurs TFP level. We also examined that the impacts of leadership's human capital on TFP are heterogeneous across different types of sub-industries.

As we verified in the first essay, technology innovation is one of the important channels to raise TFP, so we further investigate whether and how decision-makers' human capital influences corporate innovation propensity. CEO and BOD play major roles in firm's strategical decision-making, so we use their previous experiences to explore their impacts on firm's R&D investment. CEO's overseas and innovation-related experiences significantly increase R&D input ratio by around 2 and 1.5 percentage points, while production and finance experiences hinder R&D to asset ratio by 1.5-2%, respectively. The impacts magnitudes are comparable to around 75% of the average R&D input level. For board of directors, R&D ratio is notably impeded by 0.05 percent points for every 10% more BOD members with the previous government background, while marketing members promote TFP notably.

At household-level research in Chapter 4, we find that risk averse persons in general sense have lower incentives to purchase either stocks or funds with a slightly larger impact when in market downturn. After controlling for general risk attitude, financial risk aversion, reflected by lower debt tolerance, discourages both the stock and fund participation which is more sensitive towards market change than the general measure. For investment depth, general risk aversion negatively affects the investment amount in both stocks and funds with a larger and more notable impact on stocks. Financial risk aversion still impedes the investment depth of both products, but its impact on stocks is insignificant due to its sensitive reaction to market turbulence. Both types of risk attitude have relatively smaller impacts on fund due its larger risk than stock.

Our research provides empirical evidence and discussion on how to assign an innovative and efficient executive team based on members' past experiences. When assigning best-fit executives, firm should also consider its own specific features. For instance, high-tech firms focus more on inventing the tech-intensive products, so CEOs with innovation and internalization horizon are valued. The priority of traditional manufacturing firms is optimizing the operation and production process, so executives with richer general experiences are preferred. We also provide discussion on how to predict and guide household's financial behavior based on household heads' specific personality traits.

In the future research, some topics have the potentials to be further discussed. In this research, we identified the contribution magnitudes of each CEO experience on TFP (the proportion of TFP explained by certain experience). Therefore, we can get a unique aggregate human capital index for each CEO. These kinds of indices are not limited to the productivity, but also apply to other aspects, such as innovation human capital index based on R&D investment. We can adopt these indices to compare the level of innovation propensity and management capacity across individuals, so firm can use it to select a best-fit leadership based on its specific operational needs.

Appendices

APPENDIX A

APPENDICES FOR CHAPTER 2

A.1 TFP Estimation

Panel A: Definition and Descriptive Statistics for Variables in TFP Estimation

Several input/output factors are measured in money value. To keep the comparable measures, we deflate output and intermediates with Producer Price Index (PPI), and deflate capital stock with Price Indices of Investment in Fixed Assets (FAI Price Index).

Variables	Measures/Definition	2008	2012	2016
Output	Operating Revenue	1.99	2.26	2.84
Y_{it}	(Billion RMB, deflated)	(3.04)	(3.37)	(4.28)
Capital	Net Fixed Assets	0.74	0.86	1.24
K_{it}	(Billion RMB, deflated)	(1.04)	(1.43)	(2.86)
Labor	Number of Employees	2,536	2,560	2,957
L_{it}		(2,152)	(2,318)	(3,121)
Intermediate	Construction Material	1.69	1.89	2.18
M_{it}	(Billion RMB, deflated)	(2.74)	(3.07)	(3.47)

* We do not have the info of value-added, so adopting annual operating revenue to measure the output.

* PPI uses 1985 as the base year; FAI price index uses 1990 as the base year.

* Due to lacking direct measure for intermediates, we calculate it by following some Chinese literature: Intermediates = operating cost + three major expenses – employees remuneration – fixed assets depreciation.

* Statistics in the first line for each variable is the mean, and in (.) is the standard deviation.

Panel B: TFP Estimation Results

	OP	LP	ACF
ln(labor)	0.1101***	0.1026***	0.1124***
	(0.0085)	(0.0113)	(0.0014)
ln(capital)	0.0399***	0.1513***	0.0511***
	(0.0111)	(0.0218)	(0.0059)
ln(intermediates)	0.8319***	0.7214***	0.8404***
	(0.0086)	(0.0318)	(0.0033)
$\hat{\beta}_k + \hat{\beta}_l + \hat{\beta}_m$	0.9819	0.9753	1.0039

A.2 IV Selection Strategies and Assumptions in TFP Chapter

1. Baseline Model (RE-IV)

$$tfp_{i,t} = \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + \Gamma_t + c_i + \varepsilon_{i,t}$$

(1) Endogenous variables: $CEO_{i,t}$ (Overseas and functional experiences);

(2) IV selection:

- Internal IV: $IV_1 = [f\ddot{v}1_{i,t}, f\ddot{v}3_{i,t}]$;
- External IV: $IV_2 = [o_{i,t}, p_{i,t}, f_{i,t}, m_{i,t}, i_{i,t}]$.

(3) IV assumptions:

- $E\left(IV_1{}'\, CEO_{i,t}\right) \neq 0$ and $E\left(IV_2{}'\, CEO_{i,t}\right) \neq 0$;
- $E\left(IV_1' v_{i,t}\right) = 0$, where $v_{i,t} = c_i + \varepsilon_{i,t}$.

Based on the Hausman-Taylor method, all time-demeaned time-variate variables are orthogonal to the composited error, so IV_1 is uncorrelated to $v_{i,t}$:

$$E(\ddot{fv}_i'\ddot{\varepsilon}_i) = E[(Q_T fv_i)'(Q_T\varepsilon_{i,t})] = E[(Q_T fv_i)'(Q_T v_{i,t})] = E[fv_i' Q_T' v_{i,t}] = E[\ddot{fv}_i'\varepsilon_{i,t}] = 0$$

- $E(IV_2' v_{i,t}) = 0$, where $v_{i,t} = c_i + \varepsilon_{i,t}$.

2. Dynamic Panel Model (RE-IV)

$$tfp_{i,t} = \gamma \cdot tfp_{i,t-1} + \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + \Gamma_t + c_i + \varepsilon_{i,t}$$

(1) Endogenous variables:

- $CEO_{i,t}$: The same as in the static model;
- $tfp_{i,t-1}$: Due to its inclusion of c_i.

(2) IV selection:

- IV from baseline model: $IV_s = [f\ddot{v}1_{i,t}, f\ddot{v}3_{i,t}, o_{i,t}, p_{i,t}, f_{i,t}, m_{i,t}, i_{i,t}]$;
- Extra internal IV for $tfp_{i,t-1}$: $IV_3 = [\Delta tfp_{i,t-1}]$.

(3) The validity of $\Delta tfp_{i,t-1}$ (Idea from Arellano-Bover/Blundell-Bond, system-GMM)

- CEO experiences rarely change overtime, so we simply assume $\Delta CEO_{i,t} = 0$.
- By doing first-difference on dynamic panel equation for $tfp_{i,t-1}$, we have:

  $$\Delta tfp_{i,t-1} = \gamma \cdot \Delta tfp_{i,t-2} + \beta \cdot \Delta x_{i,t-1} + \Delta \varepsilon_{i,t-1}$$

  where $\beta \cdot \Delta x_{i,t-1} = \beta_2 \cdot \Delta TMT_{i,t} + \beta_3 \cdot \Delta fv_{i,t}$.
- We assume factors in previous years are independent from the future random shock:

  $$E\left(\Delta tfp_{i,t-1}^{'}\varepsilon_{i,t}\right) = E\left[\left(\gamma \cdot \Delta tfp_{i,t-2} + \beta \cdot \Delta x_{i,t-1} + \Delta \varepsilon_{i,t-1}\right)' \varepsilon_{i,t}\right] = 0$$
- By doing FD, c_i is removed from IV, so we have: $E\left(\Delta tfp_{i,t-1}^{'}c_i\right) = 0$.
- To sum up, we have: $E\left(\Delta tfp_{i,t-1}^{'}v_{i,t}\right) = E\left(\Delta tfp_{i,t-1}^{'}c_i\right) + E\left(\Delta tfp_{i,t-1}^{'}\varepsilon_{i,t}\right) = 0$.

A.3 First Stage Results of RE-IV Method

	Overseas	Production	Fin./Acc.	Marketing	Innovation
A. External and Internal Instruments					
Oversea_iv	1.0313***	0.0159	0.0135	0.0248	0.021
	(0.0438)	(0.0323)	(0.0355)	(0.0397)	(0.0435)
Production_iv	-0.0143	1.0058***	-0.0176	0.001	0.0123
	(0.0152)	(0.0289)	(0.0221)	(0.0256)	(0.0304)
Fin_acc_iv	-0.0159	-0.0141	1.0310***	0.0365	-0.0166
	(0.0169)	(0.0208)	(0.0244)	(0.0253)	(0.0229)
Marketing_iv	-0.0067	0.0238	0.0049	0.9477***	0.0568**
	(0.0141)	(0.0224)	(0.0216)	(0.0236)	(0.0257)
Innovation_iv	0.0002	-0.0114	0.0071	-0.035	0.9580***
	(0.0172)	(0.0253)	(0.0219)	(0.0251)	(0.0281)
Firm_size_demean	0.0044	-0.0137	0.0167	0.0088	0.0531***
	(0.0075)	(0.0113)	(0.0112)	(0.0126)	(0.0132)
Market_share_demean	0.0265**	0.0476**	-0.1085**	-0.0765**	-0.1049**
	(0.0135)	(0.0209)	(0.0441)	(0.0384)	(0.0469)
B. Other Existing Regressors					
$Gen\_exp_{i,t}$	-0.0040***	0.0037***	-0.0020***	-0.0078***	0.0018**
	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
$Tenure_{i,t}$	0.0012	-0.0064***	-0.0032**	-0.0120***	-0.0021
	(0.0011)	(0.0015)	(0.0015)	(0.0017)	(0.0017)
$Education\_ceo_{i,t}$	0.0159**	0.0349**	-0.0371***	-0.0666***	0.1204***
	(0.0080)	(0.0148)	(0.0137)	(0.0155)	(0.0148)
$Age\_div_{i,t}$	-0.0010***	0.0000	0.0002	-0.0009	0.0006
	(0.0003)	(0.0005)	(0.0006)	(0.0007)	(0.0007)
$Gender_{i,t}$	0.0264	-0.0284	0.0797***	-0.0032	-0.0734**
	(0.0204)	(0.0263)	(0.0264)	(0.0316)	(0.0331)
$Education\_tmt_{i,t}$	0.0439***	-0.1324***	0.0241	0.0223	0.0838***
	(0.0147)	(0.0242)	(0.0209)	(0.0243)	(0.0246)
$Tenure\_div_{i,t}$	-0.0044	0.0188	-0.0097	-0.0315**	-0.0244
	(0.0086)	(0.0126)	(0.0117)	(0.0138)	(0.0151)

(Next Page)

(Continued)					
$Firm\_size_{i,t}$	-0.0053	0.0122**	-0.004	0.0200***	-0.0497***
	(0.0042)	(0.0057)	(0.0054)	(0.0065)	(0.0066)
$Fin\_leverage_{i\ i,t-1}$	-0.0004	-0.0039**	-0.0025	-0.0034	-0.0006
	(0.0011)	(0.0019)	(0.0018)	(0.0023)	(0.0024)
$Market\_share_{i,t}$	-0.0218***	-0.0137	0.0096	-0.0446***	0.0822***
	(0.0060)	(0.0187)	(0.0205)	(0.0151)	(0.0220)
$Profitability_{,t-1}$	0.0335*	-0.0801**	0.0332	0.0294	0.0907***
	(0.0182)	(0.0352)	(0.0310)	(0.0376)	(0.0340)
$TMT\_share_{i,t}$	-0.0087	-0.0125	-0.0850***	-0.0562*	0.2011***
	(0.0230)	(0.0277)	(0.0245)	(0.0330)	(0.0365)
SOE	-0.0114*	0.013	-0.0012	0.0114	0.0230*
	(0.0069)	(0.0102)	(0.0096)	(0.0116)	(0.0119)
Big_city	-0.0032	0.0059	-0.0237***	0.0134	-0.0259**
	(0.0086)	(0.0092)	(0.0092)	(0.0121)	(0.0132)
Crisis_dum	-0.0143**	-0.0183*	-0.0206**	-0.0496***	-0.0074
	(0.0067)	(0.0097)	(0.0092)	(0.0111)	(0.0116)
_cons	0.1248***	-0.0742	0.1117**	0.2040***	0.1660***
	-0.0384	-0.0514	-0.0502	-0.0613	-0.0587
N	6718	6718	6718	6718	6718
R-squared	0.1798	0.179	0.2087	0.1825	0.1971

* The significance level: ***0.01, **0.05, *0.1.

A.4 The Classification of Sub-industry

Sub-Industry Group	National Classification Group
Sub-Indu1: Food and Beverage	Agri-Food Processing (C13) Food Producing (C14) Beverage, Liquor and Tea (C15)
Sub-Indu2: Textile	Textiles (C17) Apparel and Accessories (C18) Leather, Fur & Feathers (C19)
Sub-Indu3: Lumber and processing	Timber, Wood & Bamboo (C20) Furniture (C21)
Sub-Indu4: Culture and byproducts	Paper and Paper products (C22) Printing and Reproduction (C23) Culture/Education/Arts/Sports/Entertainment (C24)
Sub-Indu5: Raw material processing	Petroleum, Coking and Nuclear Fuel (C25) Non-metallic Mineral Products (C30) Smelting/Pressing of Ferrous Metals (C31) Smelting/Pressing of Non-ferrous Metals (C32) Metal Products (C33)
Sub-Indu6: Chemical products	Raw Chemical Materials/Products (C26) Medicines (C27) Chemical Fibers (C28) Rubber and Plastic Products (C29)
Sub-Indu7: Machinery	General Purpose Machinery (C34) Special Purpose Machinery(C35) Electrical Machinery and Apparatus (C38) Measuring Instruments/Machinery(C40)
Sub-Indu8: High tech	Computers, Communication and Electronics (C39)
Sub-Indu9: Transportation	Automobiles (C36) Railways, Shipping & Aerospace (C37)
Sub-Indu10: Other	Other Manufacturing (C41) Waste Resources Utilization (C42)

APPENDIX B

APPENDICES FOR CHAPTER 3

B.1 The Structure of the Database and Sample Firms

Panel A: The Number of Firms by Years in the Sample

Num. of Years	Frequency	Percentage
2*	3	0.19%
3	90	5.65%
4	35	2.20%
5	89	5.59%
6	177	11.11%
7	258	16.20%
8	941	59.07%

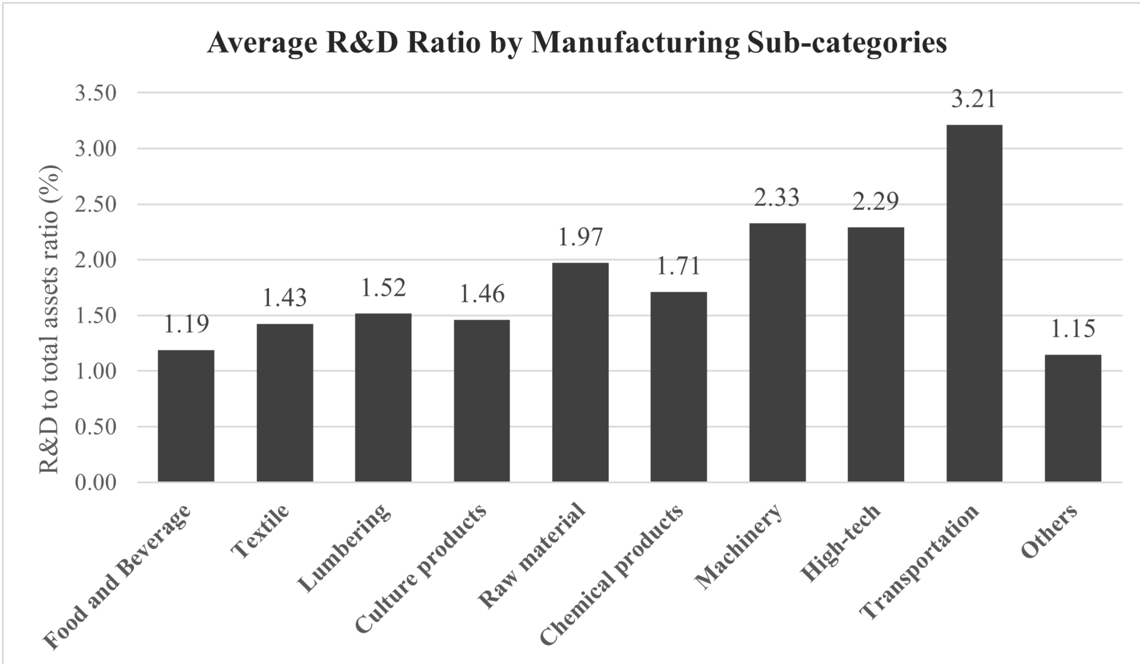
* Though we drop the two-year samples during 2008-2016, there are three firms in the dataset listed on stock market during 2009 to 2010 (they actually lasted three years in our original dataset, from 2008-2010). We keep these firms because their one and two period lagged controls are available. (the earliest available info of the controls is for the year 2007).

Panel B: The Number of Newly Entered or Delisted Firms by Year

Year	Enter	Delisted
2009	99	-
2010	257	3
2011	175	0
2012	88	3
2013	32	0
2014	90	3
2015	-	2
Total	741	11

* After dropping the one- and two-year samples, the delisted firms in 2008 and 2009 are dropped, and the newly listed firms in 2015 and 2016 are also dropped.

B.2 R&D Expenditure Ratio by Industrial Sub-categories



* The classification of sub-category in manufacturing industry is listed in Appendix A.4.

B.3 The Descriptive Statistics of CEO Turnover

Panel A: CEO Turnover by Year (Number of firms changed their CEO)

Year	Change	Not Change	Total	Percent Change
2009	151	690	841	17.95%
2010	150	800	950	15.79%
2011	170	1,030	1,200	14.17%
2012	208	1,166	1,374	15.16%
2013	233	1,225	1,458	15.98%
2014	226	1,269	1,486	15.12%
2015	264	1,317	1,581	16.70%
2016	273	1,302	1,575	17.33%
Any Change	1,001	592	1,593	62.84%

* “Any change” means if the firm changed its CEO at least once during 2009-2016.

Panel B: CEO Turnover Frequency

Times	Num. of Firms	Percent Change
0	592	37.16%
1	512	32.14%
2	343	21.53%
3	112	7.03%
4	30	1.88%
5	3	0.19%
6	1	0.06%

* “Times” means the frequency of CEO turnover during 2009-2016.

B.4 IV Selection Strategies and Assumptions in R&D Chapter

1. Baseline Model (RE-IV)

$$RD_{i,t} = \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + DYear_t + c_i + \varepsilon_{i,t}$$

(1) Endogenous variables: $CEO_{i,t}$;

(2) IV selection:

- Time-demeaned Variables: $IV_1 = [\, \ddot{fv1}_{i,t},\ \ddot{b1}_{i,t},\ \ddot{b3}_{i,t},\ \ddot{b4}_{i,t}]$;
- Lagged variables: $IV_2 = [fv1_{i,t-2},\ b1_{i,t-1},\ b2_{i,t-1},\ b3_{i,t-1},\ b4_{i,t-1}]$.

(3) IV assumptions:

- $E\,(IV_1{}'\,CEO_{i,t}) \neq 0$ and $E\,(IV_2{}'\,CEO_{i,t}) \neq 0$;
- $E\,(IV_1' v_{i,t}) = 0$, where $v_{i,t} = c_i + \varepsilon_{i,t}$.

Based on the Hausman-Taylor method, all time-demeaned time-variate variables are orthogonal to the composited error, so IV_1 is uncorrelated to $v_{i,t}$:

$$E(\ddot{fv}_i'\ddot{\varepsilon}_i) = E[(Q_T fv_i)'(Q_T\varepsilon_{i,t})] = E[(Q_T fv_i)'(Q_T v_{i,t})] = E[fv_i' Q_T' v_{i,t}] = E[\ddot{fv}_i'\varepsilon_{i,t}] = 0$$

$$E\left(B\ddot{O}D_i'\ddot{\varepsilon}_i\right) = E\left[(Q_T BOD_i)'\,(Q_T\varepsilon_{i,t})\right] = E\left[(Q_T BOD_i)'\,(Q_T v_{i,t})\right] = E[BODi'i,t] = 0$$

- $E(IV_2' v_{i,t}) = 0$, where $v_{i,t} = c_i + \varepsilon_{i,t}$.

2. Dynamic Panel Model (RE-IV)

$$RD_{i,t} = \gamma \cdot RD_{i,t-1} + \beta_1 CEO_{i,t} + \beta_2 TMT_{i,t} + \beta_3 fv_{i,t} + \beta_4 fc_i + DInd_i + DYear_t + c_i + \varepsilon_{i,t}$$

(1) Endogenous variables:

- $CEO_{i,t}$: The same as in the static model;
- $RD_{i,t-1}$: Due to its inclusion of c_i.

(2) IV selection:

- IV from the baseline model:

  $IV_s = [\ddot{fv1}_{i,t},\ \ddot{b1}_{i,t},\ \ddot{b3}_{i,t},\ \ddot{b4}_{i,t},\ fv1_{i,t-2},\ b1_{i,t-1},\ b2_{i,t-1},\ b3_{i,t-1},\ b4_{i,t-1}];$

- Extra internal IV for $RD_{i,t-1}$: $IV_3 = [\Delta RD_{i,t-1}]$.

(3) The validity of $\Delta RD_{i,t-1}$ (Idea from Arellano-Bover/Blundell-Bond, system-GMM)

- CEO experiences rarely change overtime, so we simply assume $\Delta CEO_{i,t} = 0$.

- By doing first-difference on dynamic panel equation for $RD_{i,t-1}$, we have:

$$\Delta RD_{i,t-1} = \gamma \cdot \Delta RD_{i,t-2} + \beta \cdot \Delta x_{i,t-1} + \Delta \varepsilon_{i,t-1}$$

  where $\beta \cdot \Delta x_{i,t-1} = \beta_2 \cdot \Delta BOD_{i,t} + \beta_3 \cdot \Delta fv_{i,t}$.

- We assume factors in previous years are independent from the future random shock:

  $E\left(\Delta RD'_{i,t-1}\varepsilon_{i,t}\right) = E\left[\left(\gamma \cdot \Delta RD_{i,t-2} + \beta \cdot \Delta x_{i,t-1} + \Delta\varepsilon_{i,t-1}\right)' \varepsilon_{i,t}\right] = 0$

- By doing FD, c_i is removed from the instrument, so $E(\Delta RD'_{i,t-1}c_i) = 0$.

- To sum up, we have:

  $E\left(\Delta RD'_{i,t-1}v_{i,t}\right) = E\left(\Delta RD'_{i,t-1}c_i\right) + E\left(\Delta RD'_{i,t-1}\varepsilon_{i,t}\right) = 0.$

APPENDIX C

APPENDIX FOR CHAPTER 4

C.1 Theoretical Model Specification and Derivation

1. Investment Proportion Model Setup

- Utility function: We assume a CRRA risk preference with the following utility function

$$U(W) = \frac{W^{1-\gamma}}{1-\gamma}$$

  * γ is the degree of risk aversion, $\gamma \in (-\infty, \infty)$. Larger γ implies more risk averse.
  * W is the household wealth, so $U \geq 0$ and $U(W) > 0$.

- Utility maximization:

$$max\ [(1-\pi)U(W_d) + \pi U(W_u)]$$

  * π: The possibility that the price of certain risky portfolio would go up;
  * W_i: The end-of-period wealth of the individual; $i = d$ or u, and d means the risky asset price goes down, while u means the price would go up.

- End-of-term wealth:

$$W_i = w(1-h) + wh(1-r_i) = w(1+hr_i)$$

$$U(W_i) = \frac{[w(1+hr_i)]^{1-\gamma}}{1-\gamma}, \quad i = u, d$$

  * Assuming the risk-free interest rate is 0;
  * w: Initial wealth level;
  * h: The proportion of total assets that are invested in risky assets;
  * r_i: The change rate of risky asset price, d means going down, u means going up;

- Re-write the optimization problem:

$$max\ \frac{[(1-\pi)(w(1+hr_d))^{1-\gamma} + \pi(w(1+hr_u))^{1-\gamma}]}{1-\gamma}$$

$$s.t. \quad 0 \leq \pi \leq 1, \quad 0 \leq h \leq 1$$

$$r_d < 0 < r_u$$

$$(1-\pi)r_d + \pi r_u > 0$$

- F.O.C of objective function w.r.t. h:

$$(1-\pi)(w(1+hr_d))^{1-\gamma}r_d + \pi(w(1+hr_u))^{1-\gamma}r_u = 0$$
$$h^* = \frac{1-m}{mr_u - r_d}$$

where $m = (-\frac{\pi r_u}{(1-\pi)r_d})^{-\frac{1}{\gamma}} > 0$

2. "Whether participate or not" Model Setup

- Plugging the optimal risky-asset investment proportion h^* back into the objective function in the last section, the value function would be:

$$V_p = A\frac{w^{1-\gamma}}{1-\gamma} = \frac{(A^{\frac{1}{1-\gamma}}w)^{1-\gamma}}{1-\gamma}$$

where $A = (1-\pi)(1+hr_d)^{1-\gamma} + \pi(1+hr_u)^{1-\gamma} = (\frac{r_u - r_d}{mr_u - r_d})^{1-\gamma}[(1-\pi)m^{1-\gamma} + \pi] > 0$

- The end-of-term value function of the investor $V_p = U(w_p)$, where the w_p is the end-of-term wealth. In this case, w_p can be expressed as:

$$w_p = A^{\frac{1}{1-\gamma}}w = \alpha w$$

Since $alpha = A^{\frac{1}{1-\gamma}}$ and $A > 0$, then $alpha > 0$.

- To determine whether to invest in the risk-asset, we have the criteria that the expected excess gains in wealth should be larger than the fixed cost c of risky investment:

$$w_p - w = (\alpha - 1)\, w > c$$

- We assume c has a cumulative distribution function (CDF) $G(c)$, then the potential risky-asset participation probability P is:

$$P = G[(\alpha - 1)\, w]$$

* The CDF $G(c)$ is a monotonic increasing function with c, indicating that $G'(.) > 0$.

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